## **Fixing It in Post: A Comparative Study of LLM Post-Training Data Quality and Model Performance**

## Aladin Djuhera

Technical University Munich aladin.djuhera@tum.de

**Farhan Ahmed** 

IBM Research

farhan.ahmed@ibm.com

## Heiko Ludwig

IBM Research hludwig@ibm.com

## Swanand Ravindra Kadhe

IBM Research swanand.kadhe@ibm.com szawad@ibm.com

## **Holger Boche**

**Sved Zawad** 

IBM Research

Technical University Munich boche@tum.de

**Abstract** 

Recent work on large language models (LLMs) has increasingly focused on posttraining and alignment with datasets curated to enhance instruction following, world knowledge, and specialized skills. However, most post-training datasets used in leading open- and closed-source LLMs remain inaccessible to the public, with limited information about their construction process. This lack of transparency has motivated the recent development of open-source post-training corpora. While training on these open alternatives can yield performance comparable to that of leading models, systematic comparisons remain challenging due to the significant computational cost of conducting them rigorously at scale, and are therefore largely absent. As a result, it remains unclear how specific samples, task types, or curation strategies influence downstream performance when assessing data quality. In this work, we conduct the first comprehensive side-by-side analysis of two prominent open post-training datasets: Tulu-3-SFT-Mix and SmolTalk. Using the Magpie framework, we annotate each sample with detailed quality metrics, including turn structure (single-turn vs. multi-turn), task category, input quality, and response quality, and we derive statistics that reveal structural and qualitative similarities and differences between the two datasets. Based on these insights, we design a principled curation recipe that produces a new data mixture, **TuluTalk**, which contains 14% fewer samples than either source dataset while matching or exceeding their performance on key benchmarks. Our findings offer actionable insights for constructing more effective post-training datasets that improve model performance within practical resource limits. To support future research, we publicly release both the annotated source datasets and our curated TuluTalk mixture.

## Introduction

As large language models (LLMs) models continue to grow in complexity, so do their training requirements, necessitating ever-larger datasets with each new model iteration [1–3]. While pretraining LLMs on large, general-purpose corpora is now well understood [1-6], recent work has shifted toward post-training, which includes supervised fine-tuning (SFT), reinforcement learning (RL), and task-specific fine-tuning such as domain adaptation [7–10].

Carefully curated post-training datasets play a critical role in ensuring high downstream task performance, instruction following, and advanced reasoning. Nevertheless, the majority of post-training corpora remain proprietary, restricted by commercial licensing or intellectual-property concerns, and are therefore unavailable for public scrutiny and reuse. This has motivated state-of-the-art research

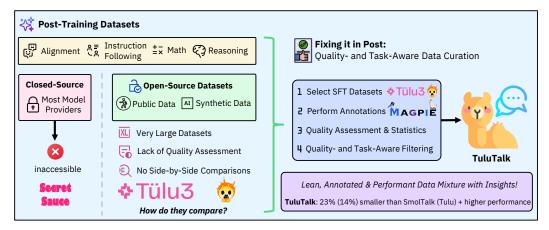


Figure 1: More effective post-training datasets through quality- and task-aware curation. We annotate and filter open-source SFT datasets (Tulu, SmolTalk) using Magpie to create TuluTalk, a leaner SFT data mixture (-23% vs. SmolTalk and -14% vs. Tulu) with improved benchmark performance.

on synthetic data generation, the development of open-source large-scale post-training datasets, and the design of effective post-training recipes [7, 11–16].

Yet, a major barrier to fully leveraging these datasets lies in the lack of systematic comparisons between them. Further, current literature employs a wide variety of model architectures, training hyperparameters, and data mixtures, resulting in considerable methodological heterogeneity across studies. Without a standardized frame of reference, it remains unclear which post-training datasets provide substantial benefits, and in what specific contexts. This lack of clarity hampers progress by obscuring the optimal direction for future research.

Another challenge with these datasets is the lack of transparent documentation regarding their curation processes. General steps are typically addressed briefly and critical details, particularly those concerning the creation of dataset mixtures, are often vaguely described. While recent works [7, 13] take giant strides in enhancing the transparency of post-training datasets and recipes, obscurity still remains for several crucial aspects. For instance, there is often a lack of details on which exact ablations were conducted to design mixture ratios, rendering the approach neither fully replicable nor sufficiently insightful to guide future dataset curation efforts.

Thus, in this paper, we adopt a principled and openly insightful approach to developing and evaluating post-training datasets, an effort that, to the best of our knowledge, is the first of its kind. To this end, we focus on two of the largest openly available SFT mixtures<sup>1</sup> from recent works: Tulu-3-SFT-Mix [7] (referred to as Tulu) and SmolTalk [9]. Our key contributions (see Fig. 1) are as follows:

- **Performance Evaluation**: We conduct the first side-by-side comparison of recent open-source SFT data mixtures: Tulu [7], SmolTalk [13], and Orca-AgentInstruct [16]. By fixing the model architecture and training hyperparameters, we enable a clean comparison of dataset performance across 14 LLM benchmarks, including those from popular Open LLM Leaderboards [17, 18]. We identify key differences and performance gaps for specialized skills such as coding, math, and instruction following, illuminating strengths and weaknesses of each mixture.
- Quality Annotations: To systematically drive data mixture decisions, we require detailed and standardized annotations of samples, a practice currently uncommon among the open-source post-training community. To this end, we leverage the Magpie framework [14] and annotate each Tulu and SmolTalk data sample along multiple dimensions, including conversational structure, prompt and response quality, and task categorization. These annotations provide concrete insights into dataset composition and support informed decision making for performant data mixtures.
- Quality-Based and Task-Aware Data Curation: Leveraging our extensive annotations, we design
  a simple yet principled curation recipe that selects high-quality and task-diverse samples from Tulu

<sup>&</sup>lt;sup>1</sup>While post-training typically includes both SFT and RL, we restrict our attention to SFT in this paper. See App. A for more details.

and SmolTalk. The resulting mixture, **TuluTalk**, contains 14% fewer samples than Tulu and 23% fewer samples than SmolTalk, offering a leaner post-training corpus while achieving comparable or better performance on key benchmarks.

Our analysis provides actionable insights for curating effective post-training datasets from open-source corpora. We publicly release our annotation code<sup>2</sup>, the corresponding annotated versions of Tulu<sup>3</sup> and SmolTalk<sup>4</sup>, as well as our curated data mixture **TuluTalk**<sup>5</sup>, to facilitate further research and enable reproducible studies on LLM post-training and data quality.

## 2 Background and Motivation

To the best of our knowledge, a direct side-by-side dissection of two flagship post-training datasets such as Tulu and SmolTalk has not been previously conducted, primarily due to significant compute requirements, particularly for large-scale SFT and extensive data annotations. We specifically select Tulu and SmolTalk (see App. B for more details on dataset compositions) due to their widespread adoption and the strong empirical performance demonstrated by their respective post-trained LLMs in recent benchmarks [7, 9].

**Tulu.** Lambert et al. [7] designed Tulu to advance broad-spectrum reasoning in medium-sized Llama models. They begin by filtering existing instruction corpora for (i) diverse real-user requests (e.g., WildChat [8], OpenAssistant [19]), and (ii) specialized skills (e.g., OpenMath-Instruct [10]). Residual gaps in *instruction following*, *math*, *coding*, and *safety* are filled with GPT-40 [20] generated prompts produced through persona-based prompting [21]. After n-gram decontamination and heuristic quality filtering, the final release contains 0.94 million high-quality pairs spanning seven broad domains (knowledge, math, reasoning, coding, safety, instruction following, and multilingual).

**SmolTalk.** Allal et al. [9] pursue a complementary objective to Tulu by building *small* models that deliver rich, multi-turn conversations without requiring large compute budgets. Their SFT mixture therefore focuses on *conversational depth* and *pragmatic rewriting*, and comprises roughly 1.04 million examples. In their curation process, they first mix Magpie-Ultra [14] which provides high-quality multi-turn prompts generated via an enhanced two-step Magpie procedure on a stronger teacher model. Second, three synthetic task-oriented subsets (Smol-Constraint, Smol-Summarization, and Smol-Rewrite [9]) are produced with targeted system prompts on Qwen2.5-72B-Instruct [22]. Third, equation-heavy math corpora [23, 24] are added. Finally, they add code-alignment and long-context resources [12, 25, 26] to the mixture. All subsets undergo a similar deduplication, quality filtering, and n-gram decontamination as in Tulu.

In addition to Tulu and SmolTalk, we also acknowledge earlier, similar-sized influential post-training mixtures such as **Orca** [15], which similarly covers tasks ranging from creative writing and text editing to coding and reading comprehension. However, initial results indicate that the more recent Tulu and SmolTalk datasets consistently outperform Orca across all evaluated tasks. Thus, we omit further investigation into Orca.

We present the corresponding SFT results in Table 1, where we fine-tune Llama-3.1-8B [27] and SmolLM2-1.7B [9] on Tulu, SmolTalk, and Orca, respectively, and evaluate both models on popular OpenLLM Leaderboard benchmarks (see App. E for the detailed fine-tuning and evaluation setup). We select these two models because they were used by Lambert et al. [7] to train the Llama-3.1-Tulu-3-8B model on the Tulu dataset and by Allal et al. [9] to train the SmolLM2-1.7B-Instruct model on SmolTalk. This choice allows us to validate our pipelines and ensure parity with prior work.

We evaluate performance across 12 tasks drawn from Open LLM Leaderboard V1 and Leaderboard V2, as well as two code generation tasks (HumanEval and HumanEval+), using the LM Evaluation Harness framework [28]. We report the average scores for Leaderboard V1 and Leaderboard V2 along with the overall average score across all 14 benchmarks. For Llama, SFT on SmolTalk outperforms Tulu on both LLM leaderboard benchmarks, however, falls behind in code benchmarks, where Tulu slightly pulls ahead on both benchmarks. Overall, fine-tuning with either dataset yields substantial

<sup>&</sup>lt;sup>2</sup>Annotation code available at: github.com/aladinD/Magpie-single-and-multi-turn

<sup>&</sup>lt;sup>3</sup>Annotated Tulu dataset: huggingface.co/datasets/aladinDJ/tulu-3-sft-mix-annotated

<sup>&</sup>lt;sup>4</sup>Annotated SmolTalk dataset: huggingface.co/datasets/aladinDJ/smoltalk-annotated

<sup>&</sup>lt;sup>5</sup>Annotated TuluTalk dataset: huggingface.co/datasets/aladinDJ/tulutalk-annotated

Table 1: SFT results for Llama-3.1-8B and SmolLM2-1.7B base models fine-tuned on Tulu, SmolTalk, and Orca, and evaluated on the Open LLM Leaderboards (averaged) and code benchmarks. The overall average is across all benchmarks. Best scores (row-wise) are in **bold**.

		Llan	na-3.1-8B			Smoll	M2-1.7B	-1.7B	
Benchmark	Base	Tulu	SmolTalk	Orca	Base	Tulu	SmolTalk	Orca	
Leaderboards									
Open LLM Leaderboard 1	58.98	62.63	65.19	60.03	48.29	50.77	51.82	47.78	
Open LLM Leaderboard 2	27.84	37.47	38.24	36.05	24.14	30.66	30.39	27.67	
Code									
HumanEval (pass@1)	34.76	58.54	54.51	51.37	0.61	1.83	1.83	0.61	
HumanEval+ (pass@1)	28.66	45.37	44.27	40.29	0.61	1.83	1.83	0.61	
Overall	41.74	50.32	51.38	47.72	31.13	35.16	35.49	32.42	

improvements compared to the baseline. For SmolLM, both SmolTalk and Tulu achieve similar performance on the OpenLLM Leaderboard benchmarks. However, performance is equally low on both code benchmarks, reflecting SmolLM's smaller size and its design focus on conversational rather than coding tasks. As noted earlier, both Tulu and SmolTalk consistently outperform Orca across all benchmarks, reflecting stronger data curation and higher corresponding task coverage.

These results prompt several initial research questions: Considering their distinct dataset compositions, what is the precise impact of SmolTalk's conversation-centric approach on fact-based benchmarks, such as math, reasoning, and code? To what extent do multi-turn conversations influence performance in these specific task categories? Lastly, how can we optimally combine Tulu and SmolTalk into a dataset mixture that enhances performance both in coding tasks and across benchmarks more broadly?

To address these questions, we conduct a detailed analysis of both post-training datasets in the following section, allowing us to make informed decisions about effective dataset combinations.

## 3 Quality Analysis of Tulu and SmolTalk via Magpie Annotations

We perform a unified diagnostic of the Tulu and SmolTalk datasets. Using the Magpie framework, a customizable self-synthesis annotation pipeline that leverages an LLM as a judge and specialized prompt templates, each data sample is systematically labeled for task category, conversation depth, instruction quality, response reward, and safety. These fine-grained annotations enable us to quantify both instruction fidelity and response adequacy, revealing precisely where these flagship corpora overlap, diverge, and, crucially, complement each other. Furthermore, this detailed characterization provides a principled basis for informed decision making regarding optimal dataset mixtures.

## 3.1 Unified Magpie Annotations

To enable direct comparability between Tulu and SmolTalk, we annotate (tag) every data sample using Magpie with Llama-3.3-70B-Instruct [27] as the judge model (see App. C.1). We find that Llamagenerated annotations are reliable and align with human judgment (see App. C.1.3 and App. C.1.4). Magpie annotates each sample with structured tags for Task Category (12 classes), Input Quality (rated from very poor to excellent), Response Quality (termed Instruct Reward, rated from 0 to 5 for multi-turn and as a real number for single-turn), Safety (assessed via Llama-Guard 2 [29]), Language, and query Difficulty. We further extend Magpie's original annotation set by explicitly capturing the conversation structure (single-turn vs. multi-turn) and retain important metadata from the original datasets (e.g., unique sample identifiers), making our annotated versions reusable for future research.

In addition, we introduce two essential extensions to Magpie (see App. C.1.2): (1) To account for inconsistent or free-form outputs, we employ an error-tolerant JSON parser and include in-context examples in each prompt, resulting in up to 15% lower post-processing errors. (2) Further, as Magpie originally evaluates only the initial user-assistant interaction, we adapt its prompts to ingest entire conversation histories for multi-turn dialogues and utilize a larger context window to prevent truncation issues and tagging failures for longer conversations. With these adaptations, we limit the annotation failure rate, i.e., samples that could not be parsed or tagged due to inconsistent formatting or residual errors, to below 3%, ensuring that at least 97% of the original dataset is reliably tagged.

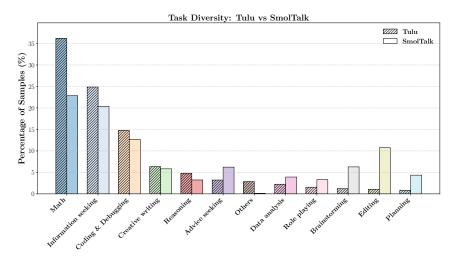
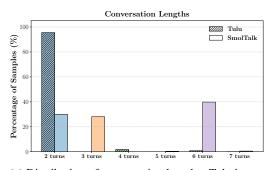
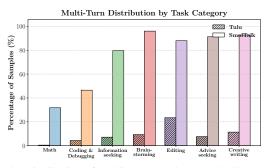


Figure 2: Task diversity in Tulu and SmolTalk as annotated by Magpie. Bars show the fraction of each dataset devoted to different tasks (e.g., math, coding/debugging). Tulu is dominated by structured, code-centric, and mathematical prompts, whereas SmolTalk features a substantial amount of conversational tasks such as editing, information seeking, and brainstorming, alongside math.





- (a) Distribution of conversation lengths: Tulu is predominantly single-turn structured (95%), whereas SmolTalk is mostly multi-turn (70%).
- (b) Distribution of multi-turn samples: SmolTalk emphasizes rich multi-turn interactions for editing, creative writing, brainstorming, and advice seeking tasks.

Figure 3: Analysis of conversational turn structure: (a) Distribution of conversation lengths (single-turn vs. multi-turn). (b) Breakdown of multi-turn samples by task category.

## 3.2 Task Categories and Turn Structure

Our task annotations in Fig. 2 reveal clear contrasts between Tulu and SmolTalk. In particular, Tulu demonstrates a strong STEM-oriented bias. Over one-third (36%) of its samples focus on math, a quarter (25%) addresses information seeking (e.g., scientific fact checking), and coding covers 15%. In contrast, conversational and creative tasks, such as editing, creative writing, brainstorming, and advice seeking, are notably underrepresented, collectively accounting for only about 10% of the data. This composition directly aligns with Tulu's primary design objective of maximizing instruction following and structured reasoning, particularly in math and code.

Conversely, SmolTalk exhibits a more conversation-centric distribution. Editing, creative writing, brainstorming, and advice seeking constitute around 30% of the dataset, significantly more than in Tulu. Although SmolTalk maintains substantial math (23%) and coding (13%) segments, its overall emphasis clearly lies in open-domain interactions, aligning with its goal of training conversationally fluent yet compact ("smol") chat models.

These differences are also reflected in the conversational turn structures shown in Fig. 3a. Tulu is predominantly single-turn (95%), while SmolTalk primarily comprises multi-turn interactions (70%). A corresponding breakdown of multi-turn samples by task category is provided in Fig. 3b. Notably, Tulu almost entirely lacks multi-turn math samples and contains only a small fraction of multi-turn

coding and information seeking samples. In contrast, SmolTalk contains multi-turn samples even for math and coding (e.g., iterative rewriting of formulas and follow-up questions), mostly sourced from Magpie-Ultra which contains 3-turn samples for coding, math, and creative tasks. We provide a more detailed analysis of turn types and conversation lengths by task category in App. C.3.

These annotation insights show that the two datasets occupy complementary regions of the instruction space: Tulu specializes in rigorous, structured problem-solving tasks, whereas SmolTalk broadens coverage through richer, more interactive conversational samples.

## 3.3 Input Quality and Instruction Reward

Fig. 4 shows the distribution of input-quality annotations for both Tulu and SmolTalk. Overall, both datasets exhibit high-quality user inputs, with more than 80% rated as either "good" or "excellent". This favorable distribution reflects the rigorous quality control measures employed during dataset curation, as both Tulu and SmolTalk use capable LLMs for data generation and employ quality checks. Nevertheless, a nonnegligible minority (10%) is rated as "poor" or "very poor", indicating either lack of context or unclear instructions (see App. C.4 for details).

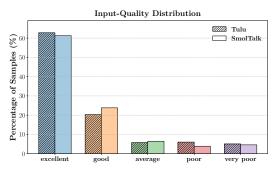
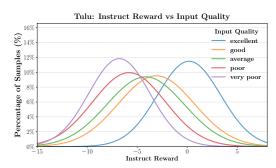


Figure 4: Distribution of input qualities: Both datasets contain over 80% good or excellent user inputs, indicating well-formulated prompts.

Additionally, we observe that LLMs face challenges in providing high-quality responses to poorly formulated user queries, which is directly reflected in their response quality. Fig. 5a and Fig. 5b show the instruct reward distribution for single-turn examples for Tulu and SmolTalk, highlighting the dependence of response quality on input quality. For both datasets, higher-quality instructions generally result in substantially better instruct rewards, indicating more helpful and contextually relevant responses from the corresponding LLMs. Examples are provided in App. C.5.3.

In contrast, multi-turn interactions follow a different trend, having "good" or "excellent" responses even if the input quality is subpar. In particular, most multi-turn samples either already have clear initial user queries, or, when ambiguity occurs, it tends to be explicitly resolved or clarified in subsequent turns. We provide concrete examples illustrating this pattern in App. C.5.3.



SmolTalk: Instruct Reward vs Input Quality

Input Quality

excellent
good
average
poor
very poor

of the property of the prope

(a) Tulu: Distribution of single-turn instruct rewards by input quality.

(b) SmolTalk: Distribution of single-turn instruct rewards by input quality.

Figure 5: Relationship between input quality and instruct reward for single-turn samples in Tulu and SmolTalk. Higher-quality instructions consistently yield higher instruct rewards (better responses).

## 3.4 Difficulty, Language, and Safety

Magpie categorizes prompts as "hard" if they involve complex reasoning or specialized domain knowledge. For instance, approximately half (50%) of the Tulu samples are labeled as "hard", followed by "easy" (21%) and "medium" (18%). The rare instances tagged as "very hard" (8%) typically involve intricate judgments, such as those concerning current political contexts. Nonetheless, difficulty annotations show minimal correlation with primary data quality indicators such as instruct reward or input quality (see App. C.6). We thus omit further investigation of difficulty tags. Similarly,

language (see App. C.7) and safety (see App. C.8) annotations exhibit negligible correlation with data quality metrics. Both datasets are overwhelmingly English (Tulu: 95%; SmolTalk: 99%) and safe (Tulu: 97%; SmolTalk: 99%).

## 4 Leveraging Annotations to Design Data Curation Recipes

In this section, we leverage our Magpie annotations to curate the Tulu and SmolTalk datasets based on the quality of inputs and responses. Specifically, our goal is to create a *quality-aware* SFT mixture by selectively combining high-quality samples from Tulu and SmolTalk.

**Ablation Setup.** We evaluate our curation recipes through ablation experiments. We use stratified sampling to extract a representative subsample of approximately 10% (about 100k examples) from each of the original Tulu and SmolTalk datasets, resulting in subsets *Tulu-100k* and *SmolTalk-100k*. A subsample size of 10% is chosen to make training more computationally efficient while preserving performance trends, as similarly demonstrated in the original Tulu experiments [7]. We apply our curation criteria to these subsamples, selecting high-quality instances to form a new data mixture.

#### 4.1 Quality-Based Curation Recipe

**Recipe.** We begin with a straightforward yet intuitive curation approach. From both Tulu and SmolTalk, we first select multi-turn samples with the highest input quality (*excellent*) and the highest reward score (5). We also select single-turn samples with the highest input quality and reward score above the median (i.e., second quantile). Applying this curation recipe to Tulu-100k and SmolTalk-100k produces a mixture of  $\sim 80$ k samples. We refer to this curated mix as *TuluTalk-80k*.

**Performance Analysis.** Table 2 compares evaluation results for TuluTalk-80k against the stratified Tulu-100k and SmolTalk-100k subsamples when fine-tuned on Llama and SmolLM models. For Llama, TuluTalk-80k generally outperforms Tulu-100k, though it remains behind SmolTalk-100k overall. TuluTalk-80k achieves the highest performance on reasoning and commonsense benchmarks. Notably, while it slightly surpasses Tulu-100k on GSM8K (66.64% vs. 65.88%), TuluTalk-80k trails in instruction following tasks (IF-Eval) by over 2%, and significantly underperforms on code benchmarks (HumanEval). For SmolLM, the trend is slightly different: Instruction following performance improves alongside GSM8K scores, but the coding tasks again tend to lag behind.

Given that LLM benchmarks predominantly emphasize coding, math, and instruction following tasks, our initial quality-based curation approach might appear overly simplistic. In particular, strict quality filtering may have skewed task diversity and inadvertently removed examples crucial for instruction following and coding, thereby negatively impacting performance on related benchmarks. We investigate this by performing a diversity analysis on Magpie's task category tags.

**Diversity Analysis.** In our preliminary analysis, instruction following emerged as a critical capability influencing performance on other benchmarks (similar observations are also reported in [7, 30]). By filtering the annotated Tulu and SmolTalk datasets for sources explicitly containing instruction following tasks, we observe that many such examples fall into the categories *advice seeking*, *information seeking*, *creative writing*, and *reasoning*. Fig. 6 illustrates the resulting task diversity across the considered datasets, highlighting significant reductions in these instruction-rich categories within TuluTalk-80k. Notably, the proportion of *information seeking* samples drops to 12% compared to 20% in SmolTalk and 25% in Tulu. This confirms that our quality-based curation recipe requires additional task-aware adaptation to include more instruction following examples.

#### 4.2 Quality-Based and Task-Aware Curation Recipe

To balance quality and task diversity, we extend our quality-based recipe by adding samples from underrepresented task categories, albeit with slightly lower quality thresholds. Specifically, we augment the previous selection with: (1) Multi-turn samples with *excellent* input quality and reward score of 5, (2) Multi-turn samples with *good* input quality and reward scores above the first quantile, and (4) Single-turn samples with *good* input quality and reward scores above the third quantile. Overall, this approach captures high-quality samples along with strategically selected samples that maintain diversity by slightly relaxing either input or output quality, resulting in 3k additional samples yielding the *TuluTalk-83k* subset. The detailed curation recipe is presented in App. D.

Table 2: SFT results for Llama-3.1-8B and SmolLM2-1.7B models fine-tuned on stratified subsets of Tulu, SmolTalk, and TuluTalk mixtures, evaluated on the Open LLM Leaderboards (averaged) and code benchmarks. The overall average is across all benchmarks. Best scores are in **bold**.

		Llama	a-3.1-8B					
Benchmark	Tulu (100k)	SmolTalk (100k)	TuluTalk (80k)	TuluTalk (83k)	Tulu (100k)	SmolTalk (100k)	TuluTalk (80k)	TuluTalk (83k)
Knowledge								
MMLU (5-shot)	63.27	62.61	63.09	62.90	48.27	49.88	49.95	49.53
MMLU-Pro (5-shot)	28.61	29.85	31.52	31.67	19.06	21.41	21.41	20.91
TruthfulQA (0-shot)	50.75	53.77	52.35	54.37	43.03	41.97	39.17	40.37
GPQA (0-shot)	30.12	29.70	28.78	28.02	29.28	27.43	26.09	27.10
Reasoning								
ARC-C (25-shot)	54.44	58.79	59.64	58.45	47.10	49.91	48.89	48.67
BBH (3-shot)	42.32	42.39	42.77	41.82	36.82	35.91	36.14	36.74
MuSR (0-shot)	42.33	39.15	37.30	37.83	34.26	35.19	33.60	34.26
Commonsense								
HellaSwag (10-shot)	60.52	62.21	62.70	62.54	40.33	42.91	44.66	42.99
WinoGrande (5-shot)	76.95	77.66	77.90	76.80	65.35	67.48	67.09	66.51
Instruction Following								
IF-Eval (0-shot)	66.03	65.66	64.38	63.94	49.13	47.90	49.19	52.50
Math								
GSM8K (5-shot)	65.88	67.70	66.64	69.45	40.33	42.91	44.66	42.99
MATH (4-shot)	10.50	7.93	8.31	8.31	3.85	3.85	3.25	3.32
Code								
HumanEval (pass@1)	50.61	52.44	48.76	51.22	1.83	1.83	1.22	1.83
HumanEval+ (pass@1)	30.61	34.51	32.43	32.44	0.61	1.22	0.61	1.22
Leaderboards								
Open LLM Leaderboard 1	61.97	63.79	63.72	64.09	49.57	50.96	50.59	50.13
Open LLM Leaderboard 2	36.65	35.78	35.51	35.26	28.73	28.62	28.28	29.14
 Overall	48.07	48.88	48.33	48.55	33.73	34.32	33.93	34.19

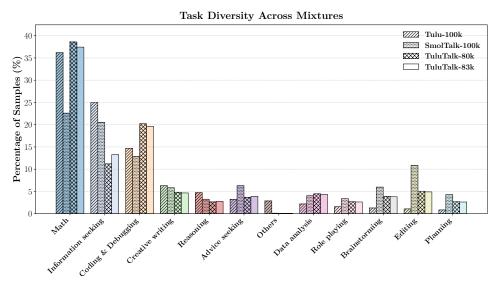


Figure 6: Task diversity distribution for stratified Tulu-100/SmolTalk-100 datasets and curated TuluTalk-80k/TuluTalk-83k mixtures. Our task-aware adaptation in TuluTalk-83k brings back 3k samples from underrepresented categories in TuluTalk, improving downstream task performance.

Table 3: SFT results for Llama-3.1-8B and SmolLM2-1.7B base models fine-tuned on Tulu, SmolTalk, Orca, and TuluTalk, evaluated on the Open LLM Leaderboards (averaged) and code benchmarks. The overall average is across all benchmarks. Best scores (row-wise) are in **bold**. Color-shaded columns highlight the TuluTalk models.

			Llama-3.1-	8B		SmolLM2-1.7B				
Benchmark	Base	Tulu	SmolTalk	Orca	TuluTalk	Base	Tulu	SmolTalk	Orca	TuluTalk
Knowledge										
MMLU (5-shot)	65.03	62.90	62.88	62.64	63.91	50.09	49.71	47.88	51.65	49.34
MMLU-Pro (5-shot)	32.71	28.73	31.76	31.89	30.17	21.26	19.61	20.37	23.40	20.67
TruthfulQA (0-shot)	45.22	46.41	55.74	52.08	53.16	36.61	44.04	44.74	42.84	43.65
GPQA (0-shot)	37.96	42.86	38.49	40.21	40.62	34.66	33.33	33.86	33.20	33.28
Reasoning										
ARC-C (25-shot)	54.69	54.61	59.04	53.07	57.42	51.54	44.54	48.46	46.25	47.27
BBH (3-shot)	46.48	39.06	45.50	45.74	43.50	34.04	36.66	37.81	38.05	38.33
MuSR (0-shot)	37.96	42.86	38.49	40.21	40.62	34.66	33.33	33.86	33.20	33.28
Commonsense										
HellaSwag (10-shot)	61.44	60.87	61.54	60.60	62.98	53.65	51.01	52.10	51.61	51.36
WinoGrande (5-shot)	76.87	76.64	77.19	71.19	79.22	68.19	65.90	65.27	64.96	66.06
Instruction Following										
IF-Eval (0-shot)	12.45	74.09	74.51	57.73	74.84	23.91	60.25	56.83	35.17	60.85
Math										
GSM8K (5-shot)	50.64	74.37	74.75	60.58	74.84	29.64	49.43	52.46	29.34	54.13
MATH (4-shot)	5.97	12.31	10.42	11.86	11.96	2.64	6.27	5.89	5.82	6.16
Code										
HumanEval (pass@1)	34.76	58.54	54.51	51.37	56.49	0.61	1.83	1.83	0.61	1.83
HumanEval+ (pass@1)	28.66	45.37	44.27	40.29	44.33	0.61	1.83	1.83	0.61	1.83
Leaderboards										
Open LLM Leaderboard 1	58.98	62.63	65.19	60.03	65.26	48.29	50.77	51.82	47.78	51.97
Open LLM Leaderboard 2	27.84	37.47	38.24	36.05	38.40	24.14	30.66	30.39	27.67	31.16
Overall	41.74	50.32	51.38	47.72	51.62	31.13	35.16	35.49	32.42	35.89

**Performance Analysis.** Table 2 compares TuluTalk-83k to previous mixtures, showing clear improvements on benchmarks where earlier versions underperformed. For the Llama model, TuluTalk-83k surpasses TuluTalk-80k by 2.8% on GSM8K (69.45% vs. 66.64%) and by 2.46% on HumanEval (51.22% vs. 48.76%). Overall, it performs slightly better than TuluTalk-80k. For the SmolLM model, TuluTalk-83k also yields higher overall performance, with the largest gain observed on IF-Eval with an improvement of 2.6%, rising from 49.19% to 52.5%. These results confirm the effectiveness of our adapted task-aware curation strategy and motivate applying our recipe to the full datasets.

## 5 Results on Full Datasets and Discussion

Building on insights from our ablations and prior analysis with smaller subsets, we apply our quality-based and task-aware data-curation recipe to the entire (annotated) SmolTalk and Tulu datasets, resulting in **TuluTalk**, a leaner SFT mixture comprising 808k samples. This represents a reduction of approximately 23% compared to SmolTalk and 14% compared to Tulu.

In Table 3, we report the SFT results for Llama and SmolLM models fine-tuned on the full Tulu, SmolTalk, Orca, and TuluTalk datasets, using the same experimental setup as before (see App. E.1 for details). On average, TuluTalk outperforms all other SFT datasets for both models.

For the Llama model, TuluTalk achieves an overall average of 51.62%, outperforming SmolTalk (51.38%), Tulu (50.32%), and significantly surpassing Orca (47.72%). In knowledge benchmarks, TuluTalk leads on MMLU at 63.91%, surpassing both Tulu and SmolTalk by 1%. While slightly behind SmolTalk on TruthfulQA, it remains competitive and outperforms SmolTalk on GPQA. On reasoning tasks, TuluTalk notably improves performance on ARC-C, achieving 57.42% (2.8% higher than Tulu), and on BBH, reaching 43.50% (4.4% higher than Tulu). Commonsense benchmarks also show clear improvements: HellaSwag at 62.98% (2.1% gain over Tulu) and WinoGrande at 79.22% (2.6% improvement over Tulu). TuluTalk further achieves the highest instruction following performance across datasets on IF-Eval, reaching 74.84%. It also demonstrates strong capabilities on math tasks, with 74.84% on GSM8K and 11.96% on the challenging MATH benchmark. Coding

Table 4: SFT results for Qwen2.5-0.5B, Qwen2.5-3B, and SmolLM3-3B base models fine-tuned on Tulu, SmolTalk, and TuluTalk, and evaluated on the Open LLM Leaderboards (averaged). The overall average is across all benchmarks. Best scores (row-wise) are in **bold**.

						,						
	Qwen2.5-0.5B			Qwen2.5-3B			SmolLM3-3B					
Benchmark	Base	Tulu	SmolTalk	TuluTalk	Base	Tulu	SmolTalk	TuluTalk	Base	Tulu	SmolTalk	TuluTalk
Leaderboards Open LLM Leaderboard 1 Open LLM Leaderboard 2		42.04 24.73	42.26 23.58	42.53 25.09	60.73 32.13	61.36 38.29	61.73 36.77	61.95 38.99	60.08 31.18	59.97 37.98	61.72 37.21	62.07 38.18
Overall	31.19	32.45	31.92	32.68	44.89	48.67	47.61	48.94	43.90	47.68	47.85	48.34

performance remains robust, with scores of 56.49% on HumanEval and 44.33% on HumanEval+. On both Open LLM Leaderboards, TuluTalk achieves top scores, surpassing both SmolTalk and Tulu.

Similarly, for the SmolLM model, TuluTalk achieves an overall average of 35.89%, exceeding SmolTalk (35.49%), Tulu (35.16%), and Orca (32.42%). TuluTalk improves notably on instruction following benchmarks (IF-Eval at 60.85%) and math tasks (e.g., GSM8K at 54.13%). Its performance in knowledge benchmarks remains competitive, though slightly behind Orca in MMLU. Reasoning benchmarks show improvements, particularly for BBH at 38.33%, leading across all other datasets. Aggregated results on the OpenLLM Leaderboards further confirm TuluTalk's leading position, surpassing all compared datasets.

Collectively, our results show that TuluTalk consistently achieves top-tier performance across diverse tasks and two models, offering significant efficiency advantages with fewer yet higher-quality samples. A detailed analysis of the corresponding training efficiency is provided in App. E.3.3.

Furthermore, to assess generalizability across model scales and architectures, we conduct additional experiments using Qwen2.5-0.5B and Qwen2.5-3B [22], as well as SmolLM3-3B [31]. Table 4 reports the Open LLM Leaderboard and overall average scores across all benchmarks for each model. The results show that TuluTalk consistently outperforms Tulu and SmolTalk across all models, confirming our prior analysis and demonstrating robust cross-model generalization. Comprehensive evaluations for each model are provided in App. E.3.4. In addition, App. E.3.5 presents results for the Llama model fine-tuned with Direct Preference Optimization (DPO) [32], further demonstrating that the performance gains observed under SFT carry over to the DPO setting.

#### 6 Conclusion

In this work, we annotated and systematically dissected the Tulu and SmolTalk post-training datasets, thoroughly quantifying their composition across multiple quality and task dimensions. Leveraging these detailed annotations, we developed a principled, quality-based, and task-aware data-curation recipe based on insights through ablations. This approach allowed us to construct *TuluTalk*, a new dataset mixture which not only significantly reduces dataset size (23% smaller than SmolTalk and 14% smaller than Tulu), but also consistently outperforms existing datasets across a comprehensive suite of benchmarks. Our results show that (1) high-quality samples, rather than sheer quantity, drive substantial performance gains, (2) differentiating single-turn from multi-turn interactions is essential for nuanced dataset curation, and (3) optimal data mixture ratios are inherently task-dependent, requiring careful balancing of quality, diversity, and representativeness. Robust evaluations conducted across multiple benchmarks and different LLM architectures ensure broad applicability of both our curation recipe and our TuluTalk mixture. By demonstrating how targeted, quality-aware curation can substantially enhance model capabilities while reducing resource demands, our work sets clear directions for future dataset curation efforts. We discuss limitations and broader impact in App. F.

## **Acknowledgments and Disclosure of Funding**

This work was supported in part by the German Federal Ministry of Education and Research (BMBF) within the research hub 6G-life (Grant 16KISK002), by the Bavarian Ministry of Science and the Arts and the Saxon Ministry for Science, Culture, and Tourism through the project Next Generation AI Computing (GAIn), by the Bavarian Ministry of Economic Affairs, Regional Development and Energy through the project 6G Future Lab Bavaria, and in part by IBM Research.

#### References

- [1] Jeffrey Li, Alex Fang, Georgios Smyrnis, Maor Ivgi, Matt Jordan, Samir Gadre, Hritik Bansal, Etash Guha, Sedrick Keh, Kushal Arora, Saurabh Garg, Rui Xin, Niklas Muennighoff, Reinhard Heckel, Jean Mercat, Mayee Chen, Suchin Gururangan, Mitchell Wortsman, Alon Albalak, Yonatan Bitton, Marianna Nezhurina, Amro Abbas, Cheng-Yu Hsieh, Dhruba Ghosh, Josh Gardner, Maciej Kilian, Hanlin Zhang, Rulin Shao, Sarah Pratt, Sunny Sanyal, Gabriel Ilharco, Giannis Daras, Kalyani Marathe, Aaron Gokaslan, Jieyu Zhang, Khyathi Chandu, Thao Nguyen, Igor Vasiljevic, Sham Kakade, Shuran Song, Sujay Sanghavi, Fartash Faghri, Sewoong Oh, Luke Zettlemoyer, Kyle Lo, Alaaeldin El-Nouby, Hadi Pouransari, Alexander Toshev, Stephanie Wang, Dirk Groeneveld, Luca Soldaini, Pang Wei Koh, Jenia Jitsev, Thomas Kollar, Alexandros G. Dimakis, Yair Carmon, Achal Dave, Ludwig Schmidt, and Vaishaal Shankar. DataComp-LM: In Search of the Next Generation of Training Sets for Language Models. *Advances in Neural Information Processing Systems*, 37:14200–14282, 2024.
- [2] Guilherme Penedo, Hynek Kydlíček, Anton Lozhkov, Margaret Mitchell, Colin A Raffel, Leandro Von Werra, Thomas Wolf, et al. The FineWeb Datasets: Decanting the Web for the Finest Text Data at Scale. Advances in Neural Information Processing Systems, 37:30811–30849, 2024.
- [3] Maurice Weber, Daniel Y Fu, Quentin Gregory Anthony, Yonatan Oren, Shane Adams, Anton Alexandrov, Xiaozhong Lyu, Huu Nguyen, Xiaozhe Yao, Virginia Adams, Ben Athiwaratkun, Rahul Chalamala, Kezhen Chen, Max Ryabinin, Tri Dao, Percy Liang, Christopher Re, Irina Rish, and Ce Zhang. RedPajama: an Open Dataset for Training Large Language Models. In *The Thirty-eight Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2024. URL https://openreview.net/forum?id=lnuXaRpwvw.
- [4] Guilherme Penedo, Quentin Malartic, Daniel Hesslow, Ruxandra Cojocaru, Hamza Alobeidli, Alessandro Cappelli, Baptiste Pannier, Ebtesam Almazrouei, and Julien Launay. The Refined-Web Dataset for Falcon LLM: Outperforming Curated Corpora with Web Data, and Web Data Only. *Advances in Neural Information Processing Systems*, 36:79155–79172, 2023.
- [5] Luca Soldaini, Rodney Kinney, Akshita Bhagia, Dustin Schwenk, David Atkinson, Russell Authur, Ben Bogin, Khyathi Chandu, Jennifer Dumas, Yanai Elazar, Valentin Hofmann, Ananya Harsh Jha, Sachin Kumar, Li Lucy, Xinxi Lyu, Nathan Lambert, Ian Magnusson, Jacob Morrison, Niklas Muennighoff, Aakanksha Naik, Crystal Nam, Matthew E. Peters, Abhilasha Ravichander, Kyle Richardson, Zejiang Shen, Emma Strubell, Nishant Subramani, Oyvind Tafjord, Pete Walsh, Luke Zettlemoyer, Noah A. Smith, Hannaneh Hajishirzi, Iz Beltagy, Dirk Groeneveld, Jesse Dodge, and Kyle Lo. Dolma: an Open Corpus of Three Trillion Tokens for Language Model Pretraining Research. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics*, pages 15725–15788. Association for Computational Linguistics, 2024.
- [6] Liping Tang, Nikhil Ranjan, Omkar Pangarkar, Xuezhi Liang, Zhen Wang, Li An, Bhaskar Rao, Linghao Jin, Huijuan Wang, Zhoujun Cheng, Suqi Sun, Cun Mu, Victor Miller, Xuezhe Ma, Yue Peng, Zhengzhong Liu, and Eric P. Xing. TxT360: A Top-Quality LLM Pre-training Dataset Requires the Perfect Blend, 2024. URL https://huggingface.co/spaces/LLM360/TxT360.
- [7] Nathan Lambert, Jacob Morrison, Valentina Pyatkin, Shengyi Huang, Hamish Ivison, Faeze Brahman, Lester James V. Miranda, Alisa Liu, Nouha Dziri, Shane Lyu, Yuling Gu, Saumya Malik, Victoria Graf, Jena D. Hwang, Jiangjiang Yang, Ronan Le Bras, Oyvind Tafjord, Chris Wilhelm, Luca Soldaini, Noah A. Smith, Yizhong Wang, Pradeep Dasigi, and Hannaneh

- Hajishirzi. Tulu 3: Pushing Frontiers in Open Language Model Post-Training, 2025. URL https://arxiv.org/abs/2411.15124.
- [8] Wenting Zhao, Xiang Ren, Jack Hessel, Claire Cardie, Yejin Choi, and Yuntian Deng. WildChat: 1M ChatGPT Interaction Logs in the Wild. In *The Twelfth International Conference on Learning Representations*, 2024. URL https://openreview.net/forum?id=B18u7ZR1bM.
- [9] Loubna Ben Allal, Anton Lozhkov, Elie Bakouch, Gabriel Martín Blázquez, Guilherme Penedo, Lewis Tunstall, Andrés Marafioti, Hynek Kydlíček, Agustín Piqueres Lajarín, Vaibhav Srivastav, Joshua Lochner, Caleb Fahlgren, Xuan-Son Nguyen, Clémentine Fourrier, Ben Burtenshaw, Hugo Larcher, Haojun Zhao, Cyril Zakka, Mathieu Morlon, Colin Raffel, Leandro von Werra, and Thomas Wolf. SmolLM2: When Smol Goes Big Data-Centric Training of a Small Language Model, 2025. URL https://arxiv.org/abs/2502.02737.
- [10] Shubham Toshniwal, Wei Du, Ivan Moshkov, Branislav Kisacanin, Alexan Ayrapetyan, and Igor Gitman. OpenMathInstruct-2: Accelerating AI for Math with Massive Open-Source Instruction Data. In *The Thirteenth International Conference on Learning Representations*, 2025. URL https://openreview.net/forum?id=mTCbq2QssD.
- [11] Loubna Ben Allal, Anton Lozhkov, Guilherme Penedo, Thomas Wolf, and Leandro von Werra. Cosmopedia, 2024. URL https://huggingface.co/datasets/HuggingFaceTB/cosmopedia.
- [12] Teknium. OpenHermes 2.5: An Open Dataset of Synthetic Data for Generalist LLM Assistants, 2023. URL https://huggingface.co/datasets/teknium/0penHermes-2.5.
- [13] Loubna Ben Allal, Anton Lozhkov, Elie Bakouch, Leandro von Werra, and Thomas Wolf. SmolLM - Blazingly Fast and Remarkably Powerful, 2024.
- [14] Zhangchen Xu, Fengqing Jiang, Luyao Niu, Yuntian Deng, Radha Poovendran, Yejin Choi, and Bill Yuchen Lin. Magpie: Alignment Data Synthesis from Scratch by Prompting Aligned LLMs with Nothing. In *The Thirteenth International Conference on Learning Representations*, 2025. URL https://openreview.net/forum?id=Pnk7vMbznK.
- [15] Subhabrata Mukherjee, Arindam Mitra, Ganesh Jawahar, Sahaj Agarwal, Hamid Palangi, and Ahmed Awadallah. Orca: Progressive Learning from Complex Explanation Traces of GPT-4, 2023. URL https://arxiv.org/abs/2306.02707.
- [16] Arindam Mitra, Luciano Del Corro, Guoqing Zheng, Shweti Mahajan, Dany Rouhana, Andres Codas, Yadong Lu, Wei ge Chen, Olga Vrousgos, Corby Rosset, Fillipe Silva, Hamed Khanpour, Yash Lara, and Ahmed Awadallah. AgentInstruct: Toward Generative Teaching with Agentic Flows, 2024. URL https://arxiv.org/abs/2407.03502.
- [17] Clémentine Fourrier, Nathan Habib, Alina Lozovskaya, Konrad Szafer, and Thomas Wolf. OpenLLM Leaderboard V1. https://huggingface.co/docs/leaderboards/en/open\_llm\_leaderboard/archive, 2023.
- [18] Clémentine Fourrier, Nathan Habib, Alina Lozovskaya, Konrad Szafer, and Thomas Wolf. Open-LLM Leaderboard V2. https://huggingface.co/spaces/open-llm-leaderboard/ open\_llm\_leaderboard, 2024.
- [19] Andreas Köpf, Yannic Kilcher, Dimitri Von Rütte, Sotiris Anagnostidis, Zhi Rui Tam, Keith Stevens, Abdullah Barhoum, Duc Nguyen, Oliver Stanley, Richárd Nagyfi, et al. Openassistant Conversations Democratizing Large Language Model Alignment. *Advances in Neural Information Processing Systems*, 36:47669–47681, 2023.
- [20] OpenAI, :, Aaron Hurst, Adam Lerer, Adam P. Goucher, Adam Perelman, Aditya Ramesh, Aidan Clark, AJ Ostrow, Akila Welihinda, Alan Hayes, Alec Radford, Aleksander Mądry, Alex Baker-Whitcomb, Alex Beutel, Alex Borzunov, Alex Carney, Alex Chow, Alex Kirillov, Alex Nichol, Alex Paino, Alex Renzin, Alex Tachard Passos, Alexander Kirillov, Alexi Christakis, Alexis Conneau, Ali Kamali, Allan Jabri, Allison Moyer, Allison Tam, Amadou Crookes, Amin Tootoochian, Amin Tootoonchian, Ananya Kumar, Andrea Vallone, Andrej Karpathy, Andrew

Braunstein, Andrew Cann, Andrew Codispoti, Andrew Galu, Andrew Kondrich, Andrew Tulloch, Andrey Mishchenko, Angela Baek, Angela Jiang, Antoine Pelisse, Antonia Woodford, Anuj Gosalia, Arka Dhar, Ashley Pantuliano, Avi Nayak, Avital Oliver, Barret Zoph, Behrooz Ghorbani, Ben Leimberger, Ben Rossen, Ben Sokolowsky, Ben Wang, Benjamin Zweig, Beth Hoover, Blake Samic, Bob McGrew, Bobby Spero, Bogo Giertler, Bowen Cheng, Brad Lightcap, Brandon Walkin, Brendan Quinn, Brian Guarraci, Brian Hsu, Bright Kellogg, Brydon Eastman, Camillo Lugaresi, Carroll Wainwright, Cary Bassin, Cary Hudson, Casey Chu, Chad Nelson, Chak Li, Chan Jun Shern, Channing Conger, Charlotte Barette, Chelsea Voss, Chen Ding, Cheng Lu, Chong Zhang, Chris Beaumont, Chris Hallacy, Chris Koch, Christian Gibson, Christina Kim, Christine Choi, Christine McLeavey, Christopher Hesse, Claudia Fischer, Clemens Winter, Coley Czarnecki, Colin Jarvis, Colin Wei, Constantin Koumouzelis, Dane Sherburn, Daniel Kappler, Daniel Levin, Daniel Levy, David Carr, David Farhi, David Mely, David Robinson, David Sasaki, Denny Jin, Dev Valladares, Dimitris Tsipras, Doug Li, Duc Phong Nguyen, Duncan Findlay, Edede Oiwoh, Edmund Wong, Ehsan Asdar, Elizabeth Proehl, Elizabeth Yang, Eric Antonow, Eric Kramer, Eric Peterson, Eric Sigler, Eric Wallace, Eugene Brevdo, Evan Mays, Farzad Khorasani, Felipe Petroski Such, Filippo Raso, Francis Zhang, Fred von Lohmann, Freddie Sulit, Gabriel Goh, Gene Oden, Geoff Salmon, Giulio Starace, Greg Brockman, Hadi Salman, Haiming Bao, Haitang Hu, Hannah Wong, Haoyu Wang, Heather Schmidt, Heather Whitney, Heewoo Jun, Hendrik Kirchner, Henrique Ponde de Oliveira Pinto, Hongyu Ren, Huiwen Chang, Hyung Won Chung, Ian Kivlichan, Ian O'Connell, Ian O'Connell, Ian Osband, Ian Silber, Ian Sohl, Ibrahim Okuyucu, Ikai Lan, Ilya Kostrikov, Ilya Sutskever, Ingmar Kanitscheider, Ishaan Gulrajani, Jacob Coxon, Jacob Menick, Jakub Pachocki, James Aung, James Betker, James Crooks, James Lennon, Jamie Kiros, Jan Leike, Jane Park, Jason Kwon, Jason Phang, Jason Teplitz, Jason Wei, Jason Wolfe, Jay Chen, Jeff Harris, Jenia Varavva, Jessica Gan Lee, Jessica Shieh, Ji Lin, Jiahui Yu, Jiayi Weng, Jie Tang, Jieqi Yu, Joanne Jang, Joaquin Quinonero Candela, Joe Beutler, Joe Landers, Joel Parish, Johannes Heidecke, John Schulman, Jonathan Lachman, Jonathan McKay, Jonathan Uesato, Jonathan Ward, Jong Wook Kim, Joost Huizinga, Jordan Sitkin, Jos Kraaijeveld, Josh Gross, Josh Kaplan, Josh Snyder, Joshua Achiam, Joy Jiao, Joyce Lee, Juntang Zhuang, Justyn Harriman, Kai Fricke, Kai Hayashi, Karan Singhal, Katy Shi, Kavin Karthik, Kayla Wood, Kendra Rimbach, Kenny Hsu, Kenny Nguyen, Keren Gu-Lemberg, Kevin Button, Kevin Liu, Kiel Howe, Krithika Muthukumar, Kyle Luther, Lama Ahmad, Larry Kai, Lauren Itow, Lauren Workman, Leher Pathak, Leo Chen, Li Jing, Lia Guy, Liam Fedus, Liang Zhou, Lien Mamitsuka, Lilian Weng, Lindsay McCallum, Lindsey Held, Long Ouyang, Louis Feuvrier, Lu Zhang, Lukas Kondraciuk, Lukasz Kaiser, Luke Hewitt, Luke Metz, Lyric Doshi, Mada Aflak, Maddie Simens, Madelaine Boyd, Madeleine Thompson, Marat Dukhan, Mark Chen, Mark Gray, Mark Hudnall, Marvin Zhang, Marwan Aljubeh, Mateusz Litwin, Matthew Zeng, Max Johnson, Maya Shetty, Mayank Gupta, Meghan Shah, Mehmet Yatbaz, Meng Jia Yang, Mengchao Zhong, Mia Glaese, Mianna Chen, Michael Janner, Michael Lampe, Michael Petrov, Michael Wu, Michele Wang, Michelle Fradin, Michelle Pokrass, Miguel Castro, Miguel Oom Temudo de Castro, Mikhail Pavlov, Miles Brundage, Miles Wang, Minal Khan, Mira Murati, Mo Bavarian, Molly Lin, Murat Yesildal, Nacho Soto, Natalia Gimelshein, Natalie Cone, Natalie Staudacher, Natalie Summers, Natan LaFontaine, Neil Chowdhury, Nick Ryder, Nick Stathas, Nick Turley, Nik Tezak, Niko Felix, Nithanth Kudige, Nitish Keskar, Noah Deutsch, Noel Bundick, Nora Puckett, Ofir Nachum, Ola Okelola, Oleg Boiko, Oleg Murk, Oliver Jaffe, Olivia Watkins, Olivier Godement, Owen Campbell-Moore, Patrick Chao, Paul McMillan, Pavel Belov, Peng Su, Peter Bak, Peter Bakkum, Peter Deng, Peter Dolan, Peter Hoeschele, Peter Welinder, Phil Tillet, Philip Pronin, Philippe Tillet, Prafulla Dhariwal, Qiming Yuan, Rachel Dias, Rachel Lim, Rahul Arora, Rajan Troll, Randall Lin, Rapha Gontijo Lopes, Raul Puri, Reah Miyara, Reimar Leike, Renaud Gaubert, Reza Zamani, Ricky Wang, Rob Donnelly, Rob Honsby, Rocky Smith, Rohan Sahai, Rohit Ramchandani, Romain Huet, Rory Carmichael, Rowan Zellers, Roy Chen, Ruby Chen, Ruslan Nigmatullin, Ryan Cheu, Saachi Jain, Sam Altman, Sam Schoenholz, Sam Toizer, Samuel Miserendino, Sandhini Agarwal, Sara Culver, Scott Ethersmith, Scott Gray, Sean Grove, Sean Metzger, Shamez Hermani, Shantanu Jain, Shengjia Zhao, Sherwin Wu, Shino Jomoto, Shirong Wu, Shuaiqi, Xia, Sonia Phene, Spencer Papay, Srinivas Narayanan, Steve Coffey, Steve Lee, Stewart Hall, Suchir Balaji, Tal Broda, Tal Stramer, Tao Xu, Tarun Gogineni, Taya Christianson, Ted Sanders, Tejal Patwardhan, Thomas Cunninghman, Thomas Degry, Thomas Dimson, Thomas Raoux, Thomas Shadwell, Tianhao Zheng, Todd Underwood, Todor Markov, Toki Sherbakov, Tom Rubin, Tom Stasi, Tomer Kaftan, Tristan Heywood, Troy Peterson, Tyce Walters, Tyna Eloundou, Valerie Qi, Veit

- Moeller, Vinnie Monaco, Vishal Kuo, Vlad Fomenko, Wayne Chang, Weiyi Zheng, Wenda Zhou, Wesam Manassra, Will Sheu, Wojciech Zaremba, Yash Patil, Yilei Qian, Yongjik Kim, Youlong Cheng, Yu Zhang, Yuchen He, Yuchen Zhang, Yujia Jin, Yunxing Dai, and Yury Malkov. GPT-4o System Card, 2024. URL https://arxiv.org/abs/2410.21276.
- [21] Tao Ge, Xin Chan, Xiaoyang Wang, Dian Yu, Haitao Mi, and Dong Yu. Scaling Synthetic Data Creation with 1,000,000,000 Personas. *arXiv* preprint arXiv:2406.20094, 2024.
- [22] Qwen, :, An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, Huan Lin, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Yang, Jiaxi Yang, Jingren Zhou, Junyang Lin, Kai Dang, Keming Lu, Keqin Bao, Kexin Yang, Le Yu, Mei Li, Mingfeng Xue, Pei Zhang, Qin Zhu, Rui Men, Runji Lin, Tianhao Li, Tianyi Tang, Tingyu Xia, Xingzhang Ren, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang, Yu Wan, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zihan Qiu. Qwen2.5 Technical Report, 2025. URL https://arxiv.org/abs/2412.15115.
- [23] Jia Li, Edward Beeching, Lewis Tunstall, Ben Lipkin, Roman Soletskyi, Shengyi Costa Huang, Kashif Rasul, Longhui Yu, Albert Jiang, Ziju Shen, Zihan Qin, Bin Dong, Li Zhou, Yann Fleureau, Guillaume Lample, and Stanislas Polu. Numina-Math. https://github.com/project-numina/aimo-progress-prize/blob/main/report/numina\_dataset.pdf, 2024.
- [24] Longhui Yu, Weisen Jiang, Han Shi, Jincheng YU, Zhengying Liu, Yu Zhang, James Kwok, Zhenguo Li, Adrian Weller, and Weiyang Liu. MetaMath: Bootstrap Your Own Mathematical Questions for Large Language Models. In *The Twelfth International Conference on Learning Representations*, 2024. URL https://openreview.net/forum?id=N8NOhgNDRt.
- [25] Yuxiang Wei, Federico Cassano, Jiawei Liu, Yifeng Ding, Naman Jain, Zachary Mueller, Harm de Vries, Leandro Von Werra, Arjun Guha, and Linming Zhang. SelfCodeAlign: Self-Alignment for Code Generation. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024. URL https://openreview.net/forum?id=xXRnUU7xTL.
- [26] Zuxin Liu, Thai Quoc Hoang, Jianguo Zhang, Ming Zhu, Tian Lan, Shirley Kokane, Juntao Tan, Weiran Yao, Zhiwei Liu, Yihao Feng, Rithesh R N, Liangwei Yang, Silvio Savarese, Juan Carlos Niebles, Huan Wang, Shelby Heinecke, and Caiming Xiong. APIGen: Automated PIpeline for Generating Verifiable and Diverse Function-Calling Datasets. In *The Thirty-eight Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2024. URL https://openreview.net/forum?id=Jfg3vw2bjx.
- [27] Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, Amy Yang, Angela Fan, Anirudh Goyal, Anthony Hartshorn, Aobo Yang, Archi Mitra, Archie Sravankumar, Artem Koreney, Arthur Hinsvark, Arun Rao, Aston Zhang, Aurelien Rodriguez, Austen Gregerson, Ava Spataru, Baptiste Roziere, Bethany Biron, Binh Tang, Bobbie Chern, Charlotte Caucheteux, Chaya Nayak, Chloe Bi, Chris Marra, Chris McConnell, Christian Keller, Christophe Touret, Chunyang Wu, Corinne Wong, Cristian Canton Ferrer, Cyrus Nikolaidis, Damien Allonsius, Daniel Song, Danielle Pintz, Danny Livshits, Danny Wyatt, David Esiobu, Dhruv Choudhary, Dhruv Mahajan, Diego Garcia-Olano, Diego Perino, Dieuwke Hupkes, Egor Lakomkin, Ehab AlBadawy, Elina Lobanova, Emily Dinan, Eric Michael Smith, Filip Radenovic, Francisco Guzmán, Frank Zhang, Gabriel Synnaeve, Gabrielle Lee, Georgia Lewis Anderson, Govind Thattai, Graeme Nail, Gregoire Mialon, Guan Pang, Guillem Cucurell, Hailey Nguyen, Hannah Korevaar, Hu Xu, Hugo Touvron, Iliyan Zarov, Imanol Arrieta Ibarra, Isabel Kloumann, Ishan Misra, Ivan Evtimov, Jack Zhang, Jade Copet, Jaewon Lee, Jan Geffert, Jana Vranes, Jason Park, Jay Mahadeokar, Jeet Shah, Jelmer van der Linde, Jennifer Billock, Jenny Hong, Jenya Lee, Jeremy Fu, Jianfeng Chi, Jianyu Huang, Jiawen Liu, Jie Wang, Jiecao Yu, Joanna Bitton, Joe Spisak, Jongsoo Park, Joseph Rocca, Joshua Johnstun, Joshua Saxe, Junteng Jia, Kalyan Vasuden Alwala, Karthik Prasad, Kartikeya Upasani, Kate Plawiak, Ke Li, Kenneth Heafield, Kevin Stone, Khalid El-Arini, Krithika Iyer, Kshitiz Malik, Kuenley Chiu, Kunal Bhalla, Kushal Lakhotia, Lauren Rantala-Yeary, Laurens van der Maaten, Lawrence Chen, Liang Tan, Liz Jenkins, Louis Martin, Lovish Madaan, Lubo Malo, Lukas Blecher, Lukas Landzaat, Luke de Oliveira, Madeline Muzzi, Mahesh Pasupuleti, Mannat Singh, Manohar Paluri, Marcin

Kardas, Maria Tsimpoukelli, Mathew Oldham, Mathieu Rita, Maya Pavlova, Melanie Kambadur, Mike Lewis, Min Si, Mitesh Kumar Singh, Mona Hassan, Naman Goyal, Narjes Torabi, Nikolay Bashlykov, Nikolay Bogoychev, Niladri Chatterji, Ning Zhang, Olivier Duchenne, Onur Celebi, Patrick Alrassy, Pengchuan Zhang, Pengwei Li, Petar Vasic, Peter Weng, Prajjwal Bhargava, Pratik Dubal, Praveen Krishnan, Punit Singh Koura, Puxin Xu, Qing He, Qingxiao Dong, Ragavan Srinivasan, Raj Ganapathy, Ramon Calderer, Ricardo Silveira Cabral, Robert Stojnic, Roberta Raileanu, Rohan Maheswari, Rohit Girdhar, Rohit Patel, Romain Sauvestre, Ronnie Polidoro, Roshan Sumbaly, Ross Taylor, Ruan Silva, Rui Hou, Rui Wang, Saghar Hosseini, Sahana Chennabasappa, Sanjay Singh, Sean Bell, Seohyun Sonia Kim, Sergey Edunov, Shaoliang Nie, Sharan Narang, Sharath Raparthy, Sheng Shen, Shengye Wan, Shruti Bhosale, Shun Zhang, Simon Vandenhende, Soumya Batra, Spencer Whitman, Sten Sootla, Stephane Collot, Suchin Gururangan, Sydney Borodinsky, Tamar Herman, Tara Fowler, Tarek Sheasha, Thomas Georgiou, Thomas Scialom, Tobias Speckbacher, Todor Mihaylov, Tong Xiao, Ujjwal Karn, Vedanuj Goswami, Vibhor Gupta, Vignesh Ramanathan, Viktor Kerkez, Vincent Gonguet, Virginie Do, Vish Vogeti, Vítor Albiero, Vladan Petrovic, Weiwei Chu, Wenhan Xiong, Wenyin Fu, Whitney Meers, Xavier Martinet, Xiaodong Wang, Xiaofang Wang, Xiaoqing Ellen Tan, Xide Xia, Xinfeng Xie, Xuchao Jia, Xuewei Wang, Yaelle Goldschlag, Yashesh Gaur, Yasmine Babaei, Yi Wen, Yiwen Song, Yuchen Zhang, Yue Li, Yuning Mao, Zacharie Delpierre Coudert, Zheng Yan, Zhengxing Chen, Zoe Papakipos, Aaditya Singh, Aayushi Srivastava, Abha Jain, Adam Kelsey, Adam Shajnfeld, Adithya Gangidi, Adolfo Victoria, Ahuva Goldstand, Ajay Menon, Ajay Sharma, Alex Boesenberg, Alexei Baevski, Allie Feinstein, Amanda Kallet, Amit Sangani, Amos Teo, Anam Yunus, Andrei Lupu, Andres Alvarado, Andrew Caples, Andrew Gu, Andrew Ho, Andrew Poulton, Andrew Ryan, Ankit Ramchandani, Annie Dong, Annie Franco, Anuj Goyal, Aparajita Saraf, Arkabandhu Chowdhury, Ashley Gabriel, Ashwin Bharambe, Assaf Eisenman, Azadeh Yazdan, Beau James, Ben Maurer, Benjamin Leonhardi, Bernie Huang, Beth Loyd, Beto De Paola, Bhargavi Paranjape, Bing Liu, Bo Wu, Boyu Ni, Braden Hancock, Bram Wasti, Brandon Spence, Brani Stojkovic, Brian Gamido, Britt Montalvo, Carl Parker, Carly Burton, Catalina Mejia, Ce Liu, Changhan Wang, Changkyu Kim, Chao Zhou, Chester Hu, Ching-Hsiang Chu, Chris Cai, Chris Tindal, Christoph Feichtenhofer, Cynthia Gao, Damon Civin, Dana Beaty, Daniel Kreymer, Daniel Li, David Adkins, David Xu, Davide Testuggine, Delia David, Devi Parikh, Diana Liskovich, Didem Foss, Dingkang Wang, Duc Le, Dustin Holland, Edward Dowling, Eissa Jamil, Elaine Montgomery, Eleonora Presani, Emily Hahn, Emily Wood, Eric-Tuan Le, Erik Brinkman, Esteban Arcaute, Evan Dunbar, Evan Smothers, Fei Sun, Felix Kreuk, Feng Tian, Filippos Kokkinos, Firat Ozgenel, Francesco Caggioni, Frank Kanayet, Frank Seide, Gabriela Medina Florez, Gabriella Schwarz, Gada Badeer, Georgia Swee, Gil Halpern, Grant Herman, Grigory Sizov, Guangyi, Zhang, Guna Lakshminarayanan, Hakan Inan, Hamid Shojanazeri, Han Zou, Hannah Wang, Hanwen Zha, Haroun Habeeb, Harrison Rudolph, Helen Suk, Henry Aspegren, Hunter Goldman, Hongyuan Zhan, Ibrahim Damlaj, Igor Molybog, Igor Tufanov, Ilias Leontiadis, Irina-Elena Veliche, Itai Gat, Jake Weissman, James Geboski, James Kohli, Janice Lam, Japhet Asher, Jean-Baptiste Gaya, Jeff Marcus, Jeff Tang, Jennifer Chan, Jenny Zhen, Jeremy Reizenstein, Jeremy Teboul, Jessica Zhong, Jian Jin, Jingyi Yang, Joe Cummings, Jon Carvill, Jon Shepard, Jonathan McPhie, Jonathan Torres, Josh Ginsburg, Junjie Wang, Kai Wu, Kam Hou U, Karan Saxena, Kartikay Khandelwal, Katayoun Zand, Kathy Matosich, Kaushik Veeraraghavan, Kelly Michelena, Keqian Li, Kiran Jagadeesh, Kun Huang, Kunal Chawla, Kyle Huang, Lailin Chen, Lakshya Garg, Lavender A, Leandro Silva, Lee Bell, Lei Zhang, Liangpeng Guo, Licheng Yu, Liron Moshkovich, Luca Wehrstedt, Madian Khabsa, Manay Avalani, Manish Bhatt, Martynas Mankus, Matan Hasson, Matthew Lennie, Matthias Reso, Maxim Groshev, Maxim Naumov, Maya Lathi, Meghan Keneally, Miao Liu, Michael L. Seltzer, Michal Valko, Michelle Restrepo, Mihir Patel, Mik Vyatskov, Mikayel Samvelyan, Mike Clark, Mike Macey, Mike Wang, Miquel Jubert Hermoso, Mo Metanat, Mohammad Rastegari, Munish Bansal, Nandhini Santhanam, Natascha Parks, Natasha White, Navyata Bawa, Nayan Singhal, Nick Egebo, Nicolas Usunier, Nikhil Mehta, Nikolay Pavlovich Laptev, Ning Dong, Norman Cheng, Oleg Chernoguz, Olivia Hart, Omkar Salpekar, Ozlem Kalinli, Parkin Kent, Parth Parekh, Paul Saab, Pavan Balaji, Pedro Rittner, Philip Bontrager, Pierre Roux, Piotr Dollar, Polina Zvyagina, Prashant Ratanchandani, Pritish Yuvraj, Oian Liang, Rachad Alao, Rachel Rodriguez, Rafi Ayub, Raghotham Murthy, Raghu Nayani, Rahul Mitra, Rangaprabhu Parthasarathy, Raymond Li, Rebekkah Hogan, Robin Battey, Rocky Wang, Russ Howes, Ruty Rinott, Sachin Mehta, Sachin Siby, Sai Jayesh Bondu, Samyak Datta, Sara Chugh, Sara Hunt, Sargun Dhillon, Sasha Sidorov, Satadru Pan, Saurabh Mahajan, Saurabh Verma, Seiji Yamamoto, Sharadh Ramaswamy, Shaun Lindsay, Shaun Lindsay, Sheng Feng, Shenghao Lin, Shengxin Cindy Zha, Shishir Patil, Shiva Shankar, Shuqiang Zhang, Shuqiang Zhang, Sinong Wang, Sneha Agarwal, Soji Sajuyigbe, Soumith Chintala, Stephanie Max, Stephen Chen, Steve Kehoe, Steve Satterfield, Sudarshan Govindaprasad, Sumit Gupta, Summer Deng, Sungmin Cho, Sunny Virk, Suraj Subramanian, Sy Choudhury, Sydney Goldman, Tal Remez, Tamar Glaser, Tamara Best, Thilo Koehler, Thomas Robinson, Tianhe Li, Tianjun Zhang, Tim Matthews, Timothy Chou, Tzook Shaked, Varun Vontimitta, Victoria Ajayi, Victoria Montanez, Vijai Mohan, Vinay Satish Kumar, Vishal Mangla, Vlad Ionescu, Vlad Poenaru, Vlad Tiberiu Mihailescu, Vladimir Ivanov, Wei Li, Wenchen Wang, Wenwen Jiang, Wes Bouaziz, Will Constable, Xiaocheng Tang, Xiaojian Wu, Xiaolan Wang, Xilun Wu, Xinbo Gao, Yaniv Kleinman, Yanjun Chen, Ye Hu, Ye Jia, Ye Qi, Yenda Li, Yilin Zhang, Ying Zhang, Yossi Adi, Youngjin Nam, Yu, Wang, Yu Zhao, Yuchen Hao, Yundi Qian, Yunlu Li, Yuzi He, Zach Rait, Zachary DeVito, Zef Rosnbrick, Zhaoduo Wen, Zhenyu Yang, Zhiwei Zhao, and Zhiyu Ma. The Llama 3 Herd of Models, 2024. URL https://arxiv.org/abs/2407.21783.

- [28] Leo Gao, Jonathan Tow, Baber Abbasi, Stella Biderman, Sid Black, Anthony DiPofi, Charles Foster, Laurence Golding, Jeffrey Hsu, Alain Le Noac'h, Haonan Li, Kyle McDonell, Niklas Muennighoff, Chris Ociepa, Jason Phang, Laria Reynolds, Hailey Schoelkopf, Aviya Skowron, Lintang Sutawika, Eric Tang, Anish Thite, Ben Wang, Kevin Wang, and Andy Zou. The Language Model Evaluation Harness, 07 2024. URL https://zenodo.org/records/12608602.
- [29] Llama Team. Meta Llama Guard 2. https://github.com/meta-llama/PurpleLlama/blob/main/Llama-Guard2/MODEL\_CARD.md, 2024.
- [30] Team Cohere, :, Aakanksha, Arash Ahmadian, Marwan Ahmed, Jay Alammar, Milad Alizadeh, Yazeed Alnumay, Sophia Althammer, Arkady Arkhangorodsky, Viraat Aryabumi, Dennis Aumiller, Raphaël Avalos, Zahara Aviv, Sammie Bae, Saurabh Baji, Alexandre Barbet, Max Bartolo, Björn Bebensee, Neeral Beladia, Walter Beller-Morales, Alexandre Bérard, Andrew Berneshawi, Anna Bialas, Phil Blunsom, Matt Bobkin, Adi Bongale, Sam Braun, Maxime Brunet, Samuel Cahyawijaya, David Cairuz, Jon Ander Campos, Cassie Cao, Kris Cao, Roman Castagné, Julián Cendrero, Leila Chan Currie, Yash Chandak, Diane Chang, Giannis Chatziveroglou, Hongyu Chen, Claire Cheng, Alexis Chevalier, Justin T. Chiu, Eugene Cho, Eugene Choi, Eujeong Choi, Tim Chung, Volkan Cirik, Ana Cismaru, Pierre Clavier, Henry Conklin, Lucas Crawhall-Stein, Devon Crouse, Andres Felipe Cruz-Salinas, Ben Cyrus, Daniel D'souza, Hugo Dalla-Torre, John Dang, William Darling, Omar Darwiche Domingues, Saurabh Dash, Antoine Debugne, Théo Dehaze, Shaan Desai, Joan Devassy, Rishit Dholakia, Kyle Duffy, Ali Edalati, Ace Eldeib, Abdullah Elkady, Sarah Elsharkawy, Irem Ergün, Beyza Ermis, Marzieh Fadaee, Boyu Fan, Lucas Fayoux, Yannis Flet-Berliac, Nick Frosst, Matthias Gallé, Wojciech Galuba, Utsav Garg, Matthieu Geist, Mohammad Gheshlaghi Azar, Ellen Gilsenan-McMahon, Seraphina Goldfarb-Tarrant, Tomas Goldsack, Aidan Gomez, Victor Machado Gonzaga, Nithya Govindarajan, Manoj Govindassamy, Nathan Grinsztajn, Nikolas Gritsch, Patrick Gu, Shangmin Guo, Kilian Haefeli, Rod Hajjar, Tim Hawes, Jingyi He, Sebastian Hofstätter, Sungjin Hong, Sara Hooker, Tom Hosking, Stephanie Howe, Eric Hu, Renjie Huang, Hemant Jain, Ritika Jain, Nick Jakobi, Madeline Jenkins, JJ Jordan, Dhruti Joshi, Jason Jung, Trushant Kalyanpur, Siddhartha Rao Kamalakara, Julia Kedrzycki, Gokce Keskin, Edward Kim, Joon Kim, Wei-Yin Ko, Tom Kocmi, Michael Kozakov, Wojciech Kryściński, Arnav Kumar Jain, Komal Kumar Teru, Sander Land, Michael Lasby, Olivia Lasche, Justin Lee, Patrick Lewis, Jeffrey Li, Jonathan Li, Hangyu Lin, Acyr Locatelli, Kevin Luong, Raymond Ma, Lukáš Mach, Marina Machado, Joanne Magbitang, Brenda Malacara Lopez, Aryan Mann, Kelly Marchisio, Olivia Markham, Alexandre Matton, Alex McKinney, Dominic McLoughlin, Jozef Mokry, Adrien Morisot, Autumn Moulder, Harry Moynehan, Maximilian Mozes, Vivek Muppalla, Lidiya Murakhovska, Hemangani Nagarajan, Alekhya Nandula, Hisham Nasir, Shauna Nehra, Josh Netto-Rosen, Daniel Ohashi, James Owers-Bardsley, Jason Ozuzu, Dennis Padilla, Gloria Park, Sam Passaglia, Jeremy Pekmez, Laura Penstone, Aleksandra Piktus, Case Ploeg, Andrew Poulton, Youran Qi, Shubha Raghvendra, Miguel Ramos, Ekagra Ranjan, Pierre Richemond, Cécile Robert-Michon, Aurélien Rodriguez, Sudip Roy, Sebastian Ruder, Laura Ruis, Louise Rust, Anubhay Sachan, Alejandro Salamanca, Kailash Karthik Sarayanakumar, Isha Satyakam, Alice Schoenauer Sebag, Priyanka Sen, Sholeh Sepehri, Preethi Seshadri, Ye Shen, Tom Sherborne, Sylvie Shang Shi, Sanal Shivaprasad, Vladyslav Shmyhlo, Anirudh Shrinivason, Inna

- Shteinbuk, Amir Shukayev, Mathieu Simard, Ella Snyder, Ava Spataru, Victoria Spooner, Trisha Starostina, Florian Strub, Yixuan Su, Jimin Sun, Dwarak Talupuru, Eugene Tarassov, Elena Tommasone, Jennifer Tracey, Billy Trend, Evren Tumer, Ahmet Üstün, Bharat Venkitesh, David Venuto, Pat Verga, Maxime Voisin, Alex Wang, Donglu Wang, Shijian Wang, Edmond Wen, Naomi White, Jesse Willman, Marysia Winkels, Chen Xia, Jessica Xie, Minjie Xu, Bowen Yang, Tan Yi-Chern, Ivan Zhang, Zhenyu Zhao, and Zhoujie Zhao. Command A: An Enterprise-Ready Large Language Model, 2025. URL https://arxiv.org/abs/2504.00698.
- [31] Elie Bakouch, Loubna Ben Allal, Anton Lozhkov, Nouamane Tazi, Lewis Tunstall, Carlos Miguel Patiño, Edward Beeching, Aymeric Roucher, Aksel Joonas Reedi, Quentin Gallouédec, Kashif Rasul, Nathan Habib, Clémentine Fourrier, Hynek Kydlicek, Guilherme Penedo, Hugo Larcher, Mathieu Morlon, Vaibhav Srivastav, Joshua Lochner, Xuan-Son Nguyen, Colin Raffel, Leandro von Werra, and Thomas Wolf. SmolLM3: Smol, Multilingual, Long-Context Reasoner. https://huggingface.co/blog/smollm3, 2025.
- [32] Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D Manning, Stefano Ermon, and Chelsea Finn. Direct Preference Optimization: Your Language Model is Secretly a Reward Model. *Advances in Neural Information Processing Systems*, 2023.
- [33] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal Policy Optimization Algorithms, 2017. URL https://arxiv.org/abs/1707.06347.
- [34] Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, Y. K. Li, Y. Wu, and Daya Guo. DeepSeekMath: Pushing the Limits of Mathematical Reasoning in Open Language Models, 2024. URL https://arxiv.org/abs/2402.03300.
- [35] Sohee Yang, Elena Gribovskaya, Nora Kassner, Mor Geva, and Sebastian Riedel. Do Large Language Models Latently Perform Multi-Hop Reasoning?, 2024. URL https://arxiv.org/ abs/2402.16837.
- [36] Shibo Hao, Sainbayar Sukhbaatar, DiJia Su, Xian Li, Zhiting Hu, Jason Weston, and Yuandong Tian. Training Large Language Models to Reason in a Continuous Latent Space, 2024. URL https://arxiv.org/abs/2412.06769.
- [37] Yujia Qin, Shihao Liang, Yining Ye, Kunlun Zhu, Lan Yan, Yaxi Lu, Yankai Lin, Xin Cong, Xiangru Tang, Bill Qian, Sihan Zhao, Lauren Hong, Runchu Tian, Ruobing Xie, Jie Zhou, Mark Gerstein, Dahai Li, Zhiyuan Liu, and Maosong Sun. ToolLLM: Facilitating Large Language Models to Master 16000+ Real-world APIs, 2023. URL https://arxiv.org/abs/2307.16789.
- [38] Yilun Du, Shuang Li, Antonio Torralba, Joshua B. Tenenbaum, and Igor Mordatch. Improving Factuality and Reasoning in Language Models through Multiagent Debate, 2023. URL https://arxiv.org/abs/2305.14325.
- [39] Akhiad Bercovich, Itay Levy, Izik Golan, Mohammad Dabbah, Ran El-Yaniv, Omri Puny, Ido Galil, Zach Moshe, Tomer Ronen, Najeeb Nabwani, Ido Shahaf, Oren Tropp, Ehud Karpas, Ran Zilberstein, Jiaqi Zeng, Soumye Singhal, Alexander Bukharin, Yian Zhang, Tugrul Konuk, Gerald Shen, Ameya Sunil Mahabaleshwarkar, Bilal Kartal, Yoshi Suhara, Olivier Delalleau, Zijia Chen, Zhilin Wang, David Mosallanezhad, Adi Renduchintala, Haifeng Qian, Dima Rekesh, Fei Jia, Somshubra Majumdar, Vahid Noroozi, Wasi Uddin Ahmad, Sean Narenthiran, Aleksander Ficek, Mehrzad Samadi, Jocelyn Huang, Siddhartha Jain, Igor Gitman, Ivan Moshkov, Wei Du, Shubham Toshniwal, George Armstrong, Branislav Kisacanin, Matvei Novikov, Daria Gitman, Evelina Bakhturina, Jane Polak Scowcroft, John Kamalu, Dan Su, Kezhi Kong, Markus Kliegl, Rabeeh Karimi, Ying Lin, Sanjeev Satheesh, Jupinder Parmar, Pritam Gundecha, Brandon Norick, Joseph Jennings, Shrimai Prabhumoye, Syeda Nahida Akter, Mostofa Patwary, Abhinav Khattar, Deepak Narayanan, Roger Waleffe, Jimmy Zhang, Bor-Yiing Su, Guyue Huang, Terry Kong, Parth Chadha, Sahil Jain, Christine Harvey, Elad Segal, Jining Huang, Sergey Kashirsky, Robert McQueen, Izzy Putterman, George Lam, Arun Venkatesan, Sherry Wu, Vinh Nguyen, Manoj Kilaru, Andrew Wang, Anna Warno, Abhilash Somasamudramath, Sandip Bhaskar, Maka Dong, Nave Assaf, Shahar Mor, Omer Ullman Argov, Scot Junkin, Oleksandr Romanenko, Pedro Larroy, Monika Katariya, Marco Rovinelli, Viji Balas, Nicholas

- Edelman, Anahita Bhiwandiwalla, Muthu Subramaniam, Smita Ithape, Karthik Ramamoorthy, Yuting Wu, Suguna Varshini Velury, Omri Almog, Joyjit Daw, Denys Fridman, Erick Galinkin, Michael Evans, Katherine Luna, Leon Derczynski, Nikki Pope, Eileen Long, Seth Schneider, Guillermo Siman, Tomasz Grzegorzek, Pablo Ribalta, Monika Katariya, Joey Conway, Trisha Saar, Ann Guan, Krzysztof Pawelec, Shyamala Prayaga, Oleksii Kuchaiev, Boris Ginsburg, Oluwatobi Olabiyi, Kari Briski, Jonathan Cohen, Bryan Catanzaro, Jonah Alben, Yonatan Geifman, Eric Chung, and Chris Alexiuk. Llama-Nemotron: Efficient Reasoning Models, 2025. URL https://arxiv.org/abs/2505.00949.
- [40] NovaSky Team. Sky-T1: Train your own O1 preview model within \$450. https://novasky-ai.github.io/posts/sky-t1, 2025.
- [41] Bespoke Labs. Bespoke-Stratos: The Unreasonable Effectiveness of Reasoning Distillation. https://www.bespokelabs.ai/blog/bespoke-stratos-the-unreasonable-effectiveness-of-reasoning-distillation, 2025.
- [42] Sathwik Tejaswi Madhusudhan, Shruthan Radhakrishna, Jash Mehta, and Toby Liang. Millions Scale Dataset Distilled from R1-32B. https://huggingface.co/datasets/ServiceNow-AI/R1-Distill-SFT, 2025.
- [43] Yingqian Min, Zhipeng Chen, Jinhao Jiang, Jie Chen, Jia Deng, Yiwen Hu, Yiru Tang, Jiapeng Wang, Xiaoxue Cheng, Huatong Song, Wayne Xin Zhao, Zheng Liu, Zhongyuan Wang, and Ji-Rong Wen. Imitate, Explore, and Self-Improve: A Reproduction Report on Slow-thinking Reasoning Systems, 2024. URL https://arxiv.org/abs/2412.09413.
- [44] Hamish Ivison, Yizhong Wang, Jiacheng Liu, Zeqiu Wu, Valentina Pyatkin, Nathan Lambert, Noah A. Smith, Yejin Choi, and Hannaneh Hajishirzi. Unpacking DPO and PPO: Disentangling Best Practices for Learning from Preference Feedback, 2024. URL https://arxiv.org/abs/2406.09279.
- [45] Genta Indra Winata, Hanyang Zhao, Anirban Das, Wenpin Tang, David D. Yao, Shi-Xiong Zhang, and Sambit Sahu. Preference Tuning with Human Feedback on Language, Speech, and Vision Tasks: A Survey, 2024. URL https://arxiv.org/abs/2409.11564.
- [46] Yushi Bai, Xin Lv, Jiajie Zhang, Yuze He, Ji Qi, Lei Hou, Jie Tang, Yuxiao Dong, and Juanzi Li. LongAlign: A Recipe for Long Context Alignment of Large Language Models. In Findings of the Association for Computational Linguistics: EMNLP 2024, 2024.
- [47] Ganqu Cui, Lifan Yuan, Ning Ding, Guanming Yao, Bingxiang He, Wei Zhu, Yuan Ni, Guotong Xie, Ruobing Xie, Yankai Lin, Zhiyuan Liu, and Maosong Sun. UltraFeedback: Boosting Language Models with Scaled AI Feedback, 2024. URL https://arxiv.org/abs/2310.01377.
- [48] Xiang Yue, Tuney Zheng, Ge Zhang, and Wenhu Chen. MAmmoTH2: Scaling Instructions from the Web, 2024. URL https://arxiv.org/abs/2405.03548.
- [49] Zhilin Wang, Yi Dong, Olivier Delalleau, Jiaqi Zeng, Gerald Shen, Daniel Egert, Jimmy J. Zhang, Makesh Narsimhan Sreedhar, and Oleksii Kuchaiev. HelpSteer2: Open-Source Dataset for Training Top-Performing Reward Models, 2024. URL https://arxiv.org/abs/2406.08673.
- [50] Hugging Face. RLHFlow-SFT-V2 Dataset. https://huggingface.co/datasets/RLHFlow/RLHFlow-SFT-Dataset-ver2, 2024.
- [51] Nazneen Rajani, Lewis Tunstall, Edward Beeching, Nathan Lambert, Alexander M. Rush, and Thomas Wolf. No Robots. https://huggingface.co/datasets/HuggingFaceH4/no\_robots, 2023.
- [52] Shayne Longpre, Le Hou, Tu Vu, Albert Webson, Hyung Won Chung, Yi Tay, Denny Zhou, Quoc V Le, Barret Zoph, Jason Wei, et al. The Flan Collection: Designing Data and Methods for Effective Instruction Tuning. *arXiv* preprint arXiv:2301.13688, 2023.

- [53] David Wadden, Kejian Shi, Jacob Morrison, Aakanksha Naik, Shruti Singh, Nitzan Barzilay, Kyle Lo, Tom Hope, Luca Soldaini, Shannon Zejiang Shen, Doug Downey, Hannaneh Hajishirzi, and Arman Cohan. SciRIFF: A Resource to Enhance Language Model Instruction-Following over Scientific Literature, 2024. URL https://arxiv.org/abs/2406.07835.
- [54] Peng Li, Yeye He, Dror Yashar, Weiwei Cui, Song Ge, Haidong Zhang, Danielle Rifinski Fainman, Dongmei Zhang, and Surajit Chaudhuri. Table-GPT: Table Fine-tuned GPT for Diverse Table Tasks. Proc. ACM Manag. Data, 2024.
- [55] Jing Luo, Longze Chen, Run Luo, Liang Zhu, Chang Ao, Jiaming Li, Yukun Chen, Xin Cheng, Wen Yang, Jiayuan Su, Ahmadreza Argha, Hamid Alinejad-Rokny, Chengming Li, Shiwen Ni, and Min Yang. PersonaMath: Boosting Mathematical Reasoning via Persona-Driven Data Augmentation, 2025. URL https://arxiv.org/abs/2410.01504.
- [56] AllenAI. Persona Algebra. https://huggingface.co/datasets/allenai/ tulu-3-sft-personas-algebra, 2024.
- [57] AllenAI. Persona Code. https://huggingface.co/datasets/allenai/tulu-3-sft-personas-code, 2024.
- [58] Ziyang Luo, Can Xu, Pu Zhao, Qingfeng Sun, Xiubo Geng, Wenxiang Hu, Chongyang Tao, Jing Ma, Qingwei Lin, and Daxin Jiang. WizardCoder: Empowering Code Large Language Models with Evol-Instruct. In The Twelfth International Conference on Learning Representations, 2024.
- [59] Xueqing Deng, Qihang Yu, Peng Wang, Xiaohui Shen, and Liang-Chieh Chen. COCONut: Modernizing COCO Segmentation, 2024. URL https://arxiv.org/abs/2404.08639.
- [60] Liwei Jiang, Kavel Rao, Seungju Han, Allyson Ettinger, Faeze Brahman, Sachin Kumar, Niloofar Mireshghallah, Ximing Lu, Maarten Sap, Yejin Choi, and Nouha Dziri. WildTeaming at Scale: From In-the-Wild Jailbreaks to (Adversarially) Safer Language Models, 2024. URL https://arxiv.org/abs/2406.18510.
- [61] Seungju Han, Kavel Rao, Allyson Ettinger, Liwei Jiang, Bill Yuchen Lin, Nathan Lambert, Yejin Choi, and Nouha Dziri. WildGuard: Open One-Stop Moderation Tools for Safety Risks, Jailbreaks, and Refusals of LLMs, 2024. URL https://arxiv.org/abs/2406.18495.
- [62] Shivalika Singh, Freddie Vargus, Daniel Dsouza, Börje F. Karlsson, Abinaya Mahendiran, Wei-Yin Ko, Herumb Shandilya, Jay Patel, Deividas Mataciunas, Laura OMahony, Mike Zhang, Ramith Hettiarachchi, Joseph Wilson, Marina Machado, Luisa Souza Moura, Dominik Krzemiński, Hakimeh Fadaei, Irem Ergün, Ifeoma Okoh, Aisha Alaagib, Oshan Mudannayake, Zaid Alyafeai, Vu Minh Chien, Sebastian Ruder, Surya Guthikonda, Emad A. Alghamdi, Sebastian Gehrmann, Niklas Muennighoff, Max Bartolo, Julia Kreutzer, Ahmet Üstün, Marzieh Fadaee, and Sara Hooker. Aya Dataset: An Open-Access Collection for Multilingual Instruction Tuning, 2024. URL https://arxiv.org/abs/2402.06619.
- [63] AllenAI. Persona IF. https://huggingface.co/datasets/allenai/tulu-3-sft-personas-instruction-following, 2024.
- [64] Álvaro Bartolomé Del Canto, Gabriel Martín Blázquez, Agustín Piqueres Lajarín, and Daniel Vila Suero. Distilabel: An AI Feedback (AIF) Framework for Building Datasets with and for LLMs. https://github.com/argilla-io/distilabel, 2024.
- [65] Hugging Face. Everyday Conversations for LLMs. https://huggingface.co/datasets/HuggingFaceTB/everyday-conversations-llama3.1-2k, 2024.
- [66] Hugging Face. Self-OSS-Starcoder2-Instruct. https://huggingface.co/datasets/bigcode/self-oss-instruct-sc2-exec-filter-50k, 2024.
- [67] Hugging Face. Cognitive Computations SystemChat 2.0. https://huggingface.co/datasets/cognitivecomputations/SystemChat-2.0, 2024.
- [68] Wan Fanqi, Huang Xinting, Yang Tao, Quan Xiaojun, Bi Wei, and Shi Shuming. Explore-Instruct: Enhancing Domain-Specific Instruction Coverage through Active Exploration, 2023.

- [69] An Yang, Baosong Yang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Zhou, Chengpeng Li, Chengyuan Li, Dayiheng Liu, Fei Huang, Guanting Dong, Haoran Wei, Huan Lin, Jialong Tang, Jialin Wang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Ma, Jianxin Yang, Jin Xu, Jingren Zhou, Jinze Bai, Jinzheng He, Junyang Lin, Kai Dang, Keming Lu, Keqin Chen, Kexin Yang, Mei Li, Mingfeng Xue, Na Ni, Pei Zhang, Peng Wang, Ru Peng, Rui Men, Ruize Gao, Runji Lin, Shijie Wang, Shuai Bai, Sinan Tan, Tianhang Zhu, Tianhao Li, Tianyu Liu, Wenbin Ge, Xiaodong Deng, Xiaohuan Zhou, Xingzhang Ren, Xinyu Zhang, Xipin Wei, Xuancheng Ren, Xuejing Liu, Yang Fan, Yang Yao, Yichang Zhang, Yu Wan, Yunfei Chu, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, Zhifang Guo, and Zhihao Fan. Qwen2 Technical Report, 2024. URL https://arxiv.org/abs/2407.10671.
- [70] Hugging Face. FsfairX-LLaMA3-RM-v0.1 . https://huggingface.co/sfairXC/FsfairX-LLaMA3-RM-v0.1, 2024.
- [71] Wei Xiong, Hanze Dong, Chenlu Ye, Ziqi Wang, Han Zhong, Heng Ji, Nan Jiang, and Tong Zhang. Iterative Preference Learning from Human Feedback: Bridging Theory and Practice for RLHF under KL-Constraint, 2024. URL https://arxiv.org/abs/2312.11456.
- [72] Hanze Dong, Wei Xiong, Deepanshu Goyal, Rui Pan, Shizhe Diao, Jipeng Zhang, Kashun Shum, and Tong Zhang. RAFT: Reward Ranked Finetuning for Generative Foundation Model Alignment. *arXiv preprint arXiv:2304.06767*, 2023.
- [73] Yifan Yao, Jinhao Duan, Kaidi Xu, Yuanfang Cai, Zhibo Sun, and Yue Zhang. A Survey on Large Language Model (LLM) Security and Privacy: The Good, the Bad, and the Ugly. *High-Confidence Computing*, page 100211, 2024.
- [74] Federico Bianchi, Mirac Suzgun, Giuseppe Attanasio, Paul Röttger, Dan Jurafsky, Tatsunori Hashimoto, and James Zou. Safety-Tuned LLaMAs: Lessons From Improving the Safety of Large Language Models that Follow Instructions, 2024. URL https://arxiv.org/abs/2309.07875.
- [75] Chia-Yi Hsu, Yu-Lin Tsai, Chih-Hsun Lin, Pin-Yu Chen, Chia-Mu Yu, and Chun-Ying Huang. Safe LoRA: the Silver Lining of Reducing Safety Risks when Fine-tuning Large Language Models, 2025. URL https://arxiv.org/abs/2405.16833.
- [76] Aladin Djuhera, Swanand Ravindra Kadhe, Farhan Ahmed, Syed Zawad, and Holger Boche. SafeMERGE: Preserving Safety Alignment in Fine-Tuned Large Language Models via Selective Layer-Wise Model Merging. In *The Thirteenth International Conference on Learning Representations. Workshop on Building Trust in LLMs*, 2025.
- [77] Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. Measuring Massive Multitask Language Understanding. *Proceedings of the International Conference on Learning Representations (ICLR)*, 2021.
- [78] Stephanie Lin, Jacob Hilton, and Owain Evans. TruthfulQA: Measuring How Models Mimic Human Falsehoods. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics*, 2022.
- [79] Mirac Suzgun, Nathan Scales, Nathanael Schärli, Sebastian Gehrmann, Yi Tay, Hyung Won Chung, Aakanksha Chowdhery, Quoc V Le, Ed H Chi, Denny Zhou, and Jason Wei. Challenging BIG-Bench Tasks and Whether Chain-of-Thought Can Solve Them. arXiv preprint arXiv:2210.09261, 2022.
- [80] Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. Think you have Solved Question Answering? Try ARC, the AI2 Reasoning Challenge. *ArXiv*, 2018.
- [81] Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. HellaSwag: Can a Machine Really Finish Your Sentence? In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 2019.
- [82] Keisuke Sakaguchi, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. WinoGrande: An Adversarial Winograd Schema Challenge at Scale. *arXiv preprint arXiv:1907.10641*, 2019.

- [83] Jeffrey Zhou, Tianjian Lu, Swaroop Mishra, Siddhartha Brahma, Sujoy Basu, Yi Luan, Denny Zhou, and Le Hou. Instruction-Following Evaluation for Large Language Models. *arXiv* preprint arXiv:2311.07911, 2023.
- [84] Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Jacob Hilton, Reiichiro Nakano, Christopher Hesse, and John Schulman. Training Verifiers to Solve Math Word Problems, 2021.
- [85] Dan Hendrycks, Collin Burns, Saurav Kadavath, Akul Arora, Steven Basart, Eric Tang, Dawn Song, and Jacob Steinhardt. Measuring Mathematical Problem Solving With the MATH Dataset. *Advances in Neural Information Processing Systems*, 2021.
- [86] Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, Alex Ray, Raul Puri, Gretchen Krueger, Michael Petrov, Heidy Khlaaf, Girish Sastry, Pamela Mishkin, Brooke Chan, Scott Gray, Nick Ryder, Mikhail Pavlov, Alethea Power, Lukasz Kaiser, Mohammad Bavarian, Clemens Winter, Philippe Tillet, Felipe Petroski Such, Dave Cummings, Matthias Plappert, Fotios Chantzis, Elizabeth Barnes, Ariel Herbert-Voss, William Hebgen Guss, Alex Nichol, Alex Paino, Nikolas Tezak, Jie Tang, Igor Babuschkin, Suchir Balaji, Shantanu Jain, William Saunders, Christopher Hesse, Andrew N. Carr, Jan Leike, Josh Achiam, Vedant Misra, Evan Morikawa, Alec Radford, Matthew Knight, Miles Brundage, Mira Murati, Katie Mayer, Peter Welinder, Bob McGrew, Dario Amodei, Sam McCandlish, Ilya Sutskever, and Wojciech Zaremba. Evaluating Large Language Models Trained on Code. arXiv, 2021.

## **NeurIPS Paper Checklist**

#### 1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [Yes]

Justification: We explain our methodology and recipe in chapters 3 and 4, and provide detailed results with discussions in Sections 4, 5 and Appendices.

#### Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

#### 2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [Yes]

Justification: Limitations are discussed in Section 6 and Appendices.

#### Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

## 3. Theory assumptions and proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [NA]

Justification: The paper focuses systematic recipe design and its empirical evaluation. Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

## 4. Experimental result reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: Detailed information on the experiments is provided in Sections 3, 4, 5 and Appendices. Code and datasets used for the analysis and results has been open sourced.

#### Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
- (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
- (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
- (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
- (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

#### 5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: Code to create the annotations and training has been provided. Annotated data and curated mixtures have also been made publicly available.

#### Guidelines

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (https://nips.cc/public/guides/CodeSubmissionPolicy) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so "No" is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (https://nips.cc/public/guides/CodeSubmissionPolicy) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new
  proposed method and baselines. If only a subset of experiments are reproducible, they
  should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

#### 6. Experimental setting/details

Question: Does the paper specify all the training and test details (e.g., data splits, hyper-parameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: Details of the experimental setup are included in Section 4 and Appendices.

## Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental
  material.

## 7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [Yes]

Justification: LLM training and evaluations are computationally expensive, therefore experiments are all run once and error bars are not available.

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).

- It should be clear whether the error bar is the standard deviation or the standard error
  of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

#### 8. Experiments compute resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: Details on the resources used and compute infrastructure are provided in the Appendices.

#### Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

#### 9. Code of ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics https://neurips.cc/public/EthicsGuidelines?

Answer: [Yes]

Justification: We have reviewed the NeurIPS Code of Ethics and conform to it to the best of our knowledge.

#### Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a
  deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

## 10. Broader impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [Yes]

Justification: Discussed in Section 6 and Appendices.

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.

- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

## 11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [No]

Justification: TulüTalk and annotated SmolTalk and Tulü3 datasets are derived from other publicly available datasets, and we do not apply specific safeguards to our released models.

#### Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

## 12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: Details are provided in Sections 3, Appendices, and the datasets' HuggingFace pages.

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.

- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

#### 13. New assets

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [Yes]

Justification: HuggingFace page containing new datasets provides documentation. Code assets also contain inline documentation.

#### Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

## 14. Crowdsourcing and research with human subjects

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [NA]

Justification: There are no crowdsourcing experiments.

#### Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

# 15. Institutional review board (IRB) approvals or equivalent for research with human subjects

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [NA]

Justification: The paper does not involve crowdsourcing nor research with human subjects Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.

• For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

## 16. Declaration of LLM usage

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

Answer: [NA]

Justification: Our recipe development does not involve LLMs as any important, original, or non-standard components

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (https://neurips.cc/Conferences/2025/LLM) for what should or should not be described.

## A Large Language Model Post-Training

While *pre-training* equips models with general linguistic and world knowledge, *post-training* refines this capability to follow user instructions, align with human preferences, and exhibit safe and helpful behavior across downstream tasks.

## A.1 Post-Training Workflow

Post-training typically consists of instruction tuning via supervised fine-tuning (SFT), followed by preference fine-tuning and reasoning alignment, often involving reinforcement learning (RL).

**Supervised Fine-Tuning (SFT).** The goal of SFT is to adapt a pre-trained model to generate helpful and relevant outputs in response to natural language instructions. This is typically achieved by training on high-quality instruction-response pairs and multi-turn conversations, sourced from either human-written or synthetic datasets. During SFT, the model learns to generalize instruction formats, task types, and conversational patterns via next-token prediction. While SFT substantially improves instruction following and task performance, it does not guarantee alignment with human preferences, especially in cases where multiple plausible responses exist. To further refine the model, preference fine-tuning (also referred to as alignment) is applied.

**Preference Fine-Tuning.** The goal of preference fine-tuning is is to align the model's output distribution with human preferences or task-specific objectives. This is typically done by guiding the model using a reward model or preference signal to prefer helpful, harmless, and honest completions. Popular algorithms for preference tuning include Proximal Policy Optimization (PPO) [33], Group Relative Policy Optimization (GRPO) [34], and Direct Preference Optimization (DPO) [32].

**Deep Thinking and Reasoning Alignment.** Recent work has explored reinforcement learning and preference-based methods to enhance *deep thinking* capabilities in LLMs, such as multi-hop reasoning [35], chain-of-thought generation [36], tool use [37], and debate-style deliberation [38]. These methods typically rely on reward models or heuristic scoring to reward structured reasoning behavior that extends beyond surface-level fluency. Corresponding reasoning-centric datasets have emerged as well [39–43], which introduce task formats that elicit step-by-step thought processes.

#### A.2 Focus on SFT

The primary goal of this paper is to analyze the quality and composition of training datasets while keeping the training procedure fixed. In particular, we focus on SFT because the performance of SFT-tuned models is largely governed by the structure and quality of the data mixture rather than by training algorithmic nuances. Furthermore, most open-source SFT pipelines follow similar training setups, whereas preference fine-tuning introduces additional complexity: the training algorithm (e.g., PPO, DPO, RLVR) directly determines the type and structure of data it can effectively utilize. For example, PPO requires preference pairs to train a reward model, followed by policy rollouts for fine-tuning [33]. DPO, by contrast, directly trains on preference pairs without requiring policy rollouts or a reward model [32]. Other methods like Reinforcement Learning with Verifiable Rewards (RLVR) require examples with verifiable numeric rewards [7].

The diversity of preference tuning recipes and their data format dependencies thus makes clean cross-method comparisons challenging. Indeed, designing and evaluating preference-based training pipelines is itself an active research area [7, 44, 45]. We leave the analysis of data quality under different alignment strategies to future work (see App. F).

Nevertheless, to assess whether our SFT curation insights transfer to preference-tuned models, we also apply DPO on Llama models fine-tuned on Tulu, SmolTalk, and our proposed TuluTalk mixture (see App. E). As shown in Table 19, the TuluTalk dataset consistently outperforms both Tulu and SmolTalk under DPO, just as it does under SFT, confirming that careful data mixture design offers robust gains across post-training stages. These results further validate our focus on dataset composition as a critical axis of post-training quality.

#### A.3 Related SFT Datasets

Tulu [7] and SmolTalk [9], investigated in this paper, are two of the most recent and widely used open-source datasets for SFT post-training of LLMs. We focus on these two datasets due to their strong reported performance over prior SFT datasets across a broad range of benchmarks when used to train the respective models introduced in their original papers.

Several other SFT datasets have been proposed in recent years, including *Orca* [16], *OpenHermes* [12], *LongAlign* [46], *UltraFeedback* [47], *MAmmoTH2* [48], *DaringAntEater* [49] *Magpie-Pro* [14] *RLHFlow-SFT-V2* [50]. While many of these datasets provide valuable capabilities, such as long-context support, synthetic feedback signals, or broad coverage across domains, Tulu and SmolTalk remain highly competitive, achieving significantly stronger performance across instruction following, reasoning, and code tasks [7, 9].

In our main paper, we compare Tulu and SmolTalk directly against Orca, demonstrating that Orca lags notably behind, particularly in code generation performance.

Furthermore, as shown in App. B, both Tulu and SmolTalk include carefully curated subsets drawn from several of the datasets mentioned above, particularly from OpenHermes2.5 [12], Smol-Magpie-Ultra [9], OpenAssistant [19], and UltraFeedback [47].

## B Dataset Composition of Tulu and SmolTalk

In this section, we provide a brief overview and composition summary of Tulu<sup>6</sup> and SmolTalk<sup>7</sup> post-training datasets.

#### B.1 Tulu

The Tulu dataset was created to bridge proprietary and open-source post-training data by leveraging publicly available datasets, persona-driven synthetic prompts, and rigorous decontamination procedures to mitigate test set leakage. Specifically, Lambert et al. [7] collected 23,327,961 candidate prompts from over 20 distinct sources, curating a multi-skill SFT corpus that comprises 939,344 samples, forming the original Tulu-3-SFT-Mix data mixture. The Tulu subsets and their respective samples can be broadly categorized into nine high-level groups:

- General: OpenAssistant (OASST1) [19], No Robots [51], WildChat [8], UltraFeedback (Tülu HC-10) [47]
- Knowledge Recall: FLAN v2 [52], SciRIFF [53], TableGPT [54]
- Math: Persona MATH, Persona MATH (Grade) [55]
- Reasoning: Persona Algebra [56], OpenMathInstruct2 [10], NuminaMath-TIR [23]
- Coding: Persona Code [57], Evol CodeAlpaca [58]
- Safety & Non-Compliance: CoCoNot [59], WildJailbreak [60], WildGuardMix [61]
- Multilingual: Aya [62]
- Precise Instruction Following: Persona IF [63]
- Other: <1,000 examples from miscellaneous small sources

## **B.2** SmolTalk

The SmolTalk dataset was developed to address the lower instruction-tuned performance of the SmolLM2 base model [9]. Specifically, Allal et al. [9] blend high-quality conversational, task-specific, math, and code datasets, filtered and generated via Distilabel [64] annotations, to cover a wide range of instruction-following capabilities. This results in a multi-domain post-training corpus of 1,043,917 training samples which is used for SFT of SmolLM2 to boost instruction following, reasoning, and conversational skills in a reproducible, open-source pipeline. The SmolTalk subsets can be similarly grouped into seven high-level categories:

- General: Everyday-Conversations [65], LongAlign [46], OpenHermes2.5 [12], Smol-Magpie-Ultra [9], Self-OSS-Starcoder-2-Instruct (Self-OSS-2) [66], SystemChats2.0 [67]
- Knowledge Recall: Smol-Summarization [9]
- Math: MetaMathQA-50k [24]
- Reasoning: NuminaMath-CoT [23]
- Coding: APIGen-80k [26]
- Safety & Non-Compliance: Smol-Constraints [9]
- Precise Instruction Following: Explore-Instruct-Rewriting [68], Smol-Rewrite [9]

We provide a detailed dataset- and sample-level breakdown of the annotated Tulu and SmolTalk datasets in Section C.

<sup>&</sup>lt;sup>6</sup>https://huggingface.co/datasets/allenai/tulu-3-sft-mixture

<sup>&</sup>lt;sup>7</sup>https://huggingface.co/datasets/HuggingFaceTB/smoltalk

## C Extended Quality Analysis

We present detailed insights and extended analyses of our annotated Tulu and SmolTalk post-training datasets, covering dataset composition, task distribution, and quality metrics.

#### C.1 Magpie Annotations

This section introduces the Magpie annotation framework and outlines our extensions to support the tagging of multi-turn conversation samples.

#### C.1.1 General Overview

Magpie [14] is a *self-synthesis* pipeline that extracts alignment annotations from open-weight, instruction-tuned LLMs without relying on seed prompts or human supervision. While Magpie can generate synthetic instruction-response pairs, we focus in this work on its *annotation* capabilities.

In particular, Magpie uses specialist judge models to annotate data samples along multiple dimensions (e.g., input quality, task category, safety), enabling scalable, automated labeling of large datasets that would be infeasible to annotate manually. This metadata can be used for filtering, stratification, or targeted analysis of the corpus.

Magpie supports the following annotation tags:

- **Input Quality** (*very poor excellent*): Measures the clarity, specificity, and structure of the prompt. Includes a textual justification.
- Task Category: Assigns each sample to one of 12 categories, including Coding & Debugging, Reasoning, Information Seeking, Brainstorming, Creative Writing, Advice Seeking, Math, Planning, Editing, Role Playing, Data Analysis, and Others.
- **Input Difficulty** (*very easy very hard*): Captures reasoning complexity and knowledge demands. Also tags *intent* (user goal) and *knowledge* (required model competence).
- Safety: Evaluated using a dedicated safety guard model.
- **Response Quality (Instruct Reward)**: Scored by a reward model based on the overall quality of the assistant's response.
- Language: Detects the language of the user input.

Magpie is fully modular such that the judge model can be substituted by any LLM in principle. By default, Magpie uses Llama-3-8B-Instruct [27] for most annotation tasks, FsfairX-LLaMA3-RM-v0.1 [14] for instruct reward scoring, and Llama-Guard 2 [29] for safety classification.

## **C.1.2** Extensions to Magpie

In its original form, Magpie does not support tagging of multi-turn conversation samples and is limited by short context windows and frequent inconsistencies in LLM outputs. To address these limitations, we extend the framework to support more robust annotation of realistic, multi-turn data.

1) Multi-Turn Adaptation. Magpie was originally designed for single-turn samples, where most annotations, such as instruct reward or input quality, are computed using only the first user-assistant exchange. However, as shown in later analysis, many multi-turn conversations undergo clarification or iterative refinement before resulting in a high-quality response. Thus, the original pipeline is insufficient for evaluating such interactions.

To support multi-turn conversations, we modify Magpie's prompts to incorporate the entire conversation history, rather than just the initial turn, and adapt reward scoring accordingly. Additionally, we raise the context window to the maximum length supported by the chosen LLM, as the default Magpie configuration sets this value conservatively low. We provide all modifications as part of our code repository<sup>8</sup>.

<sup>&</sup>lt;sup>8</sup>Code available at: github.com/aladinD/magpie-single-and-multi-turn

Multi-Turn Prompt Template: In most cases, adapting Magpie for multi-turn use simply involves replacing the single-turn user input with the full conversation history in the prompt template. Furthermore, to improve robustness under increased context length, we enforce stricter formatting by adding an in-context example and explicitly specifying the expected JSON output format. An example of these adaptations for Magpie's multi-turn task classification prompt is shown in Fig. 7.

Together with the increased context window length, this adaptation ensures that the judge model can process the full conversation history reliably.

Multi-Turn Instruct Reward: While adapting most annotation tags is straightforward, computing instruct rewards for MT conversations is more complex. Magpie uses FsfairX-LLaMA3-RM-v0.1 [14], a reward model that assigns a continuous reward score  $r^*$  to each instruction-response pair. To contextualize this score, it also computes a baseline reward  $r_{\text{base}}$  using a reference model (typically the main LLM judge) on the same instruction. The difference  $\Delta r = r^* - r_{\text{base}}$  reflects the relative improvement in response quality and is reported as the instruct reward.

This reward mechanism was originally developed for single-turn filtering and for supporting preference optimization via Magpie's DPO implementation. However, it does not generalize cleanly to MT settings, where generating a comparable baseline response for the entire conversation becomes infeasible, particularly when the number of samples in the dataset is large.

To address this, we treat ST and MT samples separately: For ST samples, we retain Magpie's original reward scoring pipeline based on the reference reward model, which is generally fast and reliable with low tagging error rates. For MT samples, we choose to avoid computing reference model-based rewards and instead use a dedicated LLM-as-a-Judge (typically the main LLM judge) to evaluate the entire conversation on a discrete scale from 0 to 5.

A unified reward annotation pipeline that applies such a judge-based scoring to both ST and MT samples is certainly feasible, but we leave its development to future work.

2) Reliable and Error Tolerant Prompts. Due to the LLM-as-a-judge nature of Magpie's annotation framework, inconsistent or free-form outputs are frequently observed. This occurs particularly when the LLM fails to follow strict formatting instructions for producing structured annotations. For example, many Magpie prompts require the model to output a score or label in a JSON-formatted response (see Fig. 7). Depending on the chosen LLM judge, inconsistencies such as <Information seeking, <INFORMATION SEEKING>, or ["information seeking"], i.e., outputs with malformed brackets and inconsistent formatting, are common. While typically benign, the original Magpie JSON parser is brittle and fails on such responses.

In addition to including in-context examples in Magpie prompts, we introduce a lightweight *forgiving* parser that replaces the original json.loads() call with a more tolerant multi-stage pipeline. Specifically, the parser performs the following:

- Brace normalization: Collapses nested braces and extracts only the first JSON block.
- **Regex-based sanitization:** Fixes unbalanced quotes, braces or backslashes, inserts missing commas, and lowercases keys via targeted regular expressions.
- Wrapper stripping: Removes Markdown fences, discards any text outside the first and last braces, and truncates after the final closing brace.
- Special-case fallback: Supports bare-number shorthands for instruct reward scoring by mapping single digits to a default score schema.
- **Graceful degradation:** Wraps parsing in try/except blocks, logs failed cases, and resets only task-specific fields without discarding the full batch.

This improved parser reliably extracts valid JSON fragments from noisy outputs, tolerating extra braces, formatting artifacts, and minor syntax violations where the original parser would simply fail. Remaining inconsistencies are rare and can be resolved through lightweight post-processing. Overall, this enhancement reduces tagging errors by up to 15%.

```
Multi-Turn Magpie Prompt for Task Classification Tagging.
# Instruction
You will be given a conversation between a User and an AI assistant.
## Conversation
\{CONVERSATION_HISTORY\}
## Tagging the Conversation
Please analyze the conversation and select the most relevant task tag
from the list below:
all_task_tags = [
    "Information seeking", # Specific information or facts
    "Reasoning",
                           # Requires logical thinking
    "Planning",
                           # Assistance in creating plans/strategies
    "Editing",
                          # Editing, rephrasing, proofreading
    "Coding & Debugging", # Writing, reviewing, or fixing code
    "Math",
                           # Math concepts, problems, and equations
    "Role playing",
                           # ChatGPT is asked to adopt a persona
    "Data analysis",
                           # Analyzing data and statistics
    "Creative writing",
                          # Writing stories, poems, or texts
    "Advice seeking",
                           # Guidance on personal/professional issues
    "Brainstorming",
                           # Generating ideas and creative thinking
    "Others"
                           # Queries that don't fit above categories
]
## Output Format:
You can only select a single primary tag. Other tags can go into
"other_tags".
  "primary_tag": "<primary tag>",
  "other_tags": ["<tag 1>", "<tag 2>", ...]
}
For instance:
"''json
}}
    "primary_tag": "Information seeking",
    "other_tags": ["Advice seeking", "Others"]
}}
...
Make sure to adhere to this formatting.
```

Figure 7: Multi-turn Magpie prompt for task classification tagging. The original prompt is extended to include the full conversation history, ensuring that all user-assistant turns are evaluated by the judge model. To improve robustness under longer context windows, the template also includes an in-context example and an explicitly specified JSON output format.

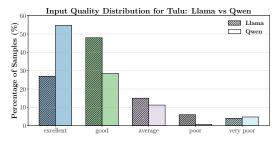
#### C.1.3 Choice of Judge Model

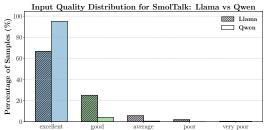
Magpie supports the use of any LLM as a potential annotation judge. In our experiments, we use Llama-3.3-70B-Instruct [27] as the primary judge model, based on two key considerations.

First, preliminary experiments with Owen-based annotators revealed systematic biases. Fig. 8a and Fig. 8b show input quality distributions on 30k stratified subsets of Tulu and SmolTalk when annotated with Llama-3.3-70B-Instruct [27] versus Qwen2-72B-Instruct [69]. In both cases, Qwen strongly over-predicts the excellent label, while Llama produces more balanced annotations. In fact, our later analysis reveals a broader spread of input quality, with samples labeled as good, excellent, and even some rated as average or poor. Owen tends to ignore these lower bands, particularly for SmolTalk, resulting in a less nuanced and potentially biased annotation profile.

Second, Magpie's default configuration uses Llama-3.1-8B-Instruct, such that much of the opensource pipeline has been tested and optimized for this model. Remaining within the same model family reduces integration friction and improves reproducibility, making the workflow more robust and accessible for the broader research community.

Based on these observations, particularly the qualitative differences in annotation quality revealed by our preliminary analysis, we select Llama-3.3-70B-Instruct as the default judge model for all annotation tasks in this study.





- offers a more realistic spread.
- (a) Input quality distribution for a 30k stratified subset (b) Input quality distribution for a 30k stratified subset of Tulu using Llama and Owen as Magpie annotators. of SmolTalk using Llama and Owen. Again, Owen Qwen strongly favors the *excellent* label, while Llama exhibits a strong upward bias toward *excellent* input quality labels, unlike Llama which is more balanced.

Figure 8: Comparison of input quality annotations produced by Llama-3.3-70B-Instruct and Qwen2-72B-Instruct judge models on 30k stratified subsets of Tulu and SmolTalk. Owen consistently over-predicts high-quality labels, while Llama provides a more balanced distribution.

#### C.1.4 Human Evaluation of Annotation Quality

In addition to comparing different judge models, we perform a systematic manual inspection of a small subset of annotated samples to assess alignment between LLM-generated annotations and human judgment. To this end, we stratify 100 TuluTalk samples by task category and have four authors independently review 25 samples each for input quality and instruct reward. We then compute exact-match agreement and Spearman's rank correlation ( $\rho$ ) between the LLM annotations and the human consensus. Table 5 shows that both input quality and instruct reward exhibit high categorical agreement ( $\geq 90\%$ ) and strong positive rank correlation, indicating that the LLM's annotations closely align with human judgments. Most disagreements involve one-step differences (e.g., rating input quality as excellent versus good), likely reflecting subjective variation. Overall, these results confirm that a capable judge model, specifically the Llama-3.3-70B-Instruct used in our study, can reliably approximate expert annotations for both fine- and coarse-grained annotation tasks.

Table 5: Evaluation of annotation quality for 100 stratified TuluTalk samples: Exact-match agreement and Spearman's rank correlation  $(\rho)$  indicate strong alignment between LLM and human judgment.

<b>Annotation Category</b>	Agreement (%)	Spearman $(\rho)$
Input Quality	91	0.85
Instruct Reward	93	0.87

## **C.2** Annotated Dataset Composition

Tables 6 and 7 provide an overview of the dataset-level composition by category and source subset after performing Magpie annotations.

**Tulu.** After tagging, the annotated Tulu dataset comprises 911,782 samples, resulting in a loss of only 3% samples due to tagging errors. In general, the dominant categories are *Math*, *Coding*, and *Reasoning*, where *Math* is notably overrepresented with 21.5% of samples. Other categories are more evenly distributed, with category shares ranging between 10-12%. Further, *Precise Instruction Following* appears surprisingly limited, making up only 3.3% of the dataset. *Other* samples are negligible, constituting just 0.1% of the total samples.

**SmolTalk.** After tagging, the annotated SmolTalk dataset comprises 1,024,791 samples, with a tagging failure rate of only 2%, resulting in minimal data loss. For SmolTalk, the dominant category is *General*, accounting for 57.6% of all samples. Within this category, the majority of samples stem from the *Smol-Magpie-Ultra* subset (39.8%), which contains multi-turn synthetic conversations designed to enhance open-domain fluency and context handling. This emphasis on general-purpose data is a deliberate curation choice aimed at bootstrapping conversational fluency, tone control, and context length generalization in *Smol* models. Notably, the *Math* and *Coding* categories are significantly underrepresented, comprising only 4.6% and 7.1% of the dataset, respectively, thus suggesting potential limitations in STEM-related reasoning coverage.

Magpie annotations allow us to build on this high-level dataset categorization with a more rigorous, fine-grained *sample-level* analysis in the following sections.

Table 6: Dataset-level composition of the annotated Tulu dataset after Magpie tagging, showing the number of samples, dataset share, and share within each task category.

Category	Prompt Dataset	# Samples	Dataset %	Category %	
	No Robots	8 703	1.0%		
General	OASST1	7 117	0.8%	12.2%	
General	Tülu HC-10	210	0.0%	12.270	
	WildChat	94 470	10.4%		
	FLAN v2	89 828	9.9%		
Knowledge Recall	SciRIFF	9719	1.1%	11.5%	
_	TableGPT	4 962	0.5%		
M .1	Persona MATH	145 895	16.0%	21.50	
Math	Persona MATH (Grade)	49 973	5.5%	21.5%	
	NuminaMath-TIR	56 699	6.2%		
Reasoning	OpenMathInstruct2	49 997	5.5%	13.8%	
	Persona Algebra	19 439	2.1%		
	Evol CodeAlpaca	106 882	11.7%	15.507	
Coding	Persona Code	34 987	3.8%	15.5%	
	CoCoNot	10 977	1.2%		
Safety & Non-Compliance	Synth+WildGuardMix	50 190	5.5%	12.2%	
	WildJailbreak	49 998	5.5%		
Multilingual	Aya	91 003	10.0%	10.0%	
Precise Instruction Following	Persona IF	29 938	3.3%	3.3%	
Other	Other	795	0.1%	0.1%	
Total	20 datasets	911 782	100.0%	100.0%	

Table 7: Dataset-level composition of the annotated SmolTalk dataset after Magpie tagging, showing the number of samples, dataset share, and share within each task category.

Category	Prompt Dataset	# Samples	Dataset %	Category %
	Everyday-Conversations	2 249	0.2%	
	LongAlign	3 5 1 1	0.3%	
General	OpenHermes2.5	94 439	9.2%	57.6%
General	Smol-Magpie-Ultra	407 971	39.8%	37.0%
	Self-OSS-2	48 085	4.7%	
	SystemChats2.0	34 120	3.3%	
Knowledge Recall	Smol-Summarization	96 322	9.4%	9.4%
Math	MetaMathQA-50k	46 728	4.6%	4.6%
Reasoning	Numina-CoT	100 982	9.9%	9.9%
Coding	APIGen-80k	72 522	7.1%	7.1%
Safety & Non-Compliance	Smol-Constraints	34 175	3.3%	3.3%
Presing Instruction Following	Explore-Instruct-Rewriting	30 384	3.0%	8.2%
Precise Instruction Following	Smol-Rewrite	53 303	5.2%	8.2%
Total	13 datasets	1 024 791	100.0%	100.0%

## **C.2.1** Token Length Distribution

To examine the token length distribution across the post-training datasets, we binned the per-sample token counts for both Tulu and SmolTalk (fine-tuned with Llama models) into 40 logarithmically spaced intervals ranging from  $2^4$  (16) to  $2^{13}$  (8,192) tokens. Fig. 9 and Fig. 10 show the resulting token length distributions across source subsets for Tulu and SmolTalk, respectively. Notably, different prompt sources exhibit distinct token length profiles, which can influence batch size, memory requirements, and learning dynamics when mixed during training. This variation in token lengths motivates our use of a sum-reduction over token-level losses, rather than the more commonly used mean-reduction (see App. E). A more in-depth discussion of this analysis is provided in Lambert et al. [7]. In our subsequent analysis, we do not further investigate token length characteristics, but include this section here for completeness.

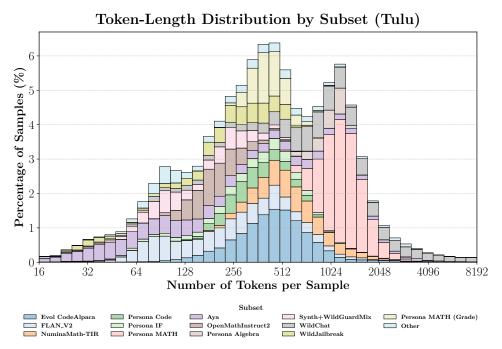


Figure 9: Token length distribution per post-training subset for Tulu. Synth+WildGuardMix and WildChat subsets feature the longest token lengths.

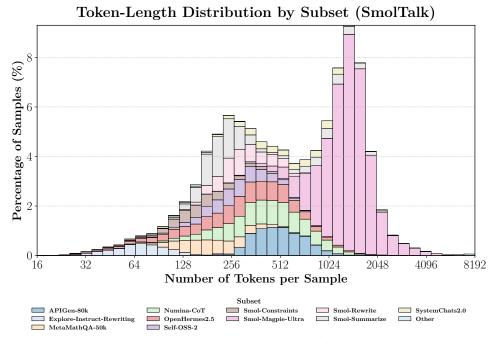


Figure 10: Token length distribution per post-training subset for SmolTalk. Smol-Magpie-Ultra features longer conversations and thus increased token lengths.

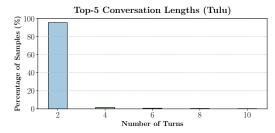
### **C.3** Turn Types and Conversation Lengths

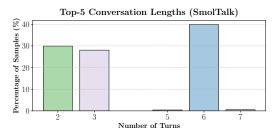
# C.3.1 Single-Turn vs. Multi-Turn Samples

Tulu and SmolTalk differ substantially in the distribution of single-turn (ST) and multi-turn (MT) samples. Fig. 11 shows the corresponding top-5 conversation lengths for both datasets.

**Tulu.** ST samples (i.e., 2 message exchanges in total between user and assistant) dominate the Tulu dataset, comprising 870,819 examples (95.5% of the data), compared to only 40,963 MT examples (4.5% of the data). Among MT samples, 4-turn conversations (i.e., a single follow-up) represent approximately 1.8% of the dataset. All higher-turn conversations individually account for less than 0.8% (see Fig. 11a). Thus, Tulu is an overwhelmingly *single-turn dataset*.

**SmolTalk.** In contrast, MT samples constitute the majority of SmolTalk, with 718,164 examples (70% of the data), while ST samples make up the remaining 306,627 (30% of the data). Within MT examples, 6-turn conversations dominate, accounting for approximately 39.8% of samples, followed by 3-turn conversations (mostly sourced from the *Smol-Magpie-Ultra* subset) at 28% of the data. All other turn counts are negligible, each contributing less than 0.5%. Consequently, SmolTalk is an overwhelmingly *multi-turn dataset*.





- (a) Tulu: the majority of samples are single-turn.
- (b) SmolTalk: the majority of samples are multi-turn.

Figure 11: Distribution of the top-5 conversation lengths. Tulu is overwhelmingly single-turn, whereas SmolTalk is predominantly multi-turn, albeit with a substantial single-turn segment.

### C.3.2 Turn Type per Task Category

Tables 8 and 9 compare the distribution of ST and MT samples across Magpie task categories for Tulu and SmolTalk. This constitutes a *sample-level* view of how different task categories are distributed across single-turn and multi-turn interactions.

**Tulu.** All Magpie task categories in Tulu are heavily skewed toward single-turn interactions, with *Math*, *Information Seeking*, and *Coding* contributing the largest shares of ST samples. The highest multi-turn proportion is found in the *Information Seeking* category, where samples often reflect users iteratively refining or clarifying their queries to guide the LLM's response. Fig. 12 visualizes the relative ST and MT proportions across task categories for Tulu.

Table 8: Sample-level distribution of Single-turn (ST) vs. multi-turn (MT) examples in the annotated Tulu dataset by Magpie task category: (a) shows the relative proportion of ST/MT samples within each category, while (b) shows the category-wise share among all ST and MT samples, respectively.

(a) Relative composition within each task category (row-wise).

(b) Distribution across ST and MT splits (columnwise).

Category	ST %	MT %	Total %
Advice seeking	92.4	7.6	100.0
Brainstorming	90.7	9.3	100.0
Coding & Debugging	95.7	4.3	100.0
Creative writing	88.6	11.4	100.0
Data analysis	97.3	2.7	100.0
Editing	76.6	23.4	100.0
Information seeking	92.9	7.1	100.0
Math	99.5	0.5	100.0
Other	97.5	2.5	100.0
Planning	92.4	7.6	100.0
Reasoning	97.6	2.4	100.0
Role playing	82.7	17.3	100.0

Category	ST %	MT %
Advice seeking	3.1	5.5
Brainstorming	1.2	2.6
Coding & Debugging	14.8	14.2
Creative writing	5.9	16.1
Data analysis	2.3	1.4
Editing	0.9	5.6
Information seeking	24.2	39.5
Math	37.7	3.7
Others	2.9	1.6
Planning	0.8	1.4
Reasoning	4.9	2.6
Role playing	1.4	6.0
Total	100.0	100.0

**SmolTalk.** All Magpie task categories in SmolTalk exhibit a strong skew toward multi-turn interactions. Notably, *Brainstorming*, *Role Playing*, and *Creative Writing* exceed 90% MT samples, reflecting their inherently conversational nature. *Coding & Debugging* and *Math* show the highest relative single-turn proportions (53.6% and 68.0%) of their respective categories (see Table 9a), indicating a prevalence of one-shot problem-solution pairs. When viewed within each turn-type split (see Table 9b), *Math* dominates the single-turn subset (51.7% of all ST samples), while *Information Seeking* leads among multi-turn samples (23.4% of MT samples). These patterns suggest that well-defined tasks often occur in single interactions, whereas more exploratory or research-oriented queries tend to span multiple turns. Fig. 13 visualizes the ST/MT distribution across task categories in SmolTalk.

Table 9: Sample-level distribution of Single-turn (ST) vs. multi-turn (MT) examples in the annotated SmolTalk dataset by Magpie task category: (a) shows the relative proportion of ST/MT samples within each category, while (b) shows the category-wise share among all ST and MT samples, respectively.

(a) Relative composition within each task category (row-wise).

(b) Distribution across ST and MT splits (columnwise).

Category	ST %	MT %	Total %
Advice seeking	8.3	91.7	100.0
Brainstorming	3.4	96.6	100.0
Coding & Debugging	53.6	46.4	100.0
Creative writing	7.0	93.0	100.0
Data analysis	4.2	95.8	100.0
Editing	12.3	87.7	100.0
Information seeking	20.3	79.7	100.0
Math	68.0	32.0	100.0
Others	6.0	94.0	100.0
Planning	4.7	95.3	100.0
Reasoning	12.9	87.1	100.0
Role playing	2.8	97.2	100.0

Category	ST %	MT %
Advice seeking	1.7	8.1
Brainstorming	0.7	8.4
Coding & Debugging	23.0	8.4
Creative writing	1.4	7.7
Data analysis	0.6	5.4
Editing	4.5	13.6
Information seeking	14.0	23.4
Math	51.7	10.3
Others	0.0	0.2
Planning	0.7	5.9
Reasoning	1.4	4.1
Role playing	0.3	4.6
Total	100.0	100.0

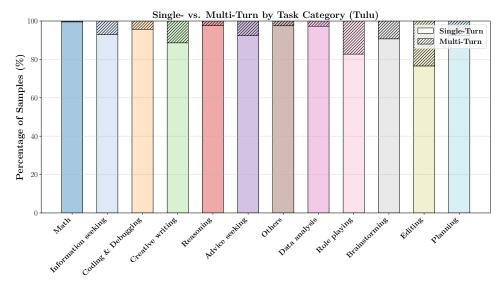


Figure 12: Turn type distribution in Tulu by Magpie task category. Most categories are dominated by single-turn (ST) samples, reflecting the dataset's focus on concise, one-shot interactions.

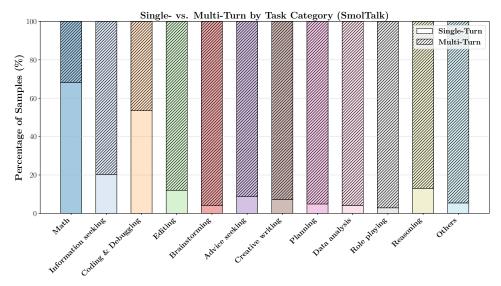


Figure 13: Turn type distribution in SmolTalk by Magpie task category. Most categories are dominated by multi-turn (MT) samples, consistent with the dataset's emphasis on dialogic interaction. *Math* stands out with a higher proportion of single-turn, one-shot problem-solution exchanges.

### **C.4** Input Quality Analysis

Magpie rates the input quality, i.e., the quality of the initial user prompt in a user–assistant exchange, on a five-point scale ranging from "very poor" to "excellent". Specifically, it assesses whether the user query is clearly formulated such that a language model can understand it and generate an appropriate, high-quality response.

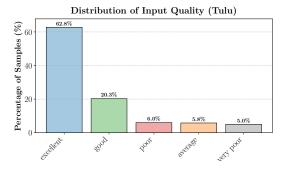
#### C.4.1 Overall Input Quality Distribution

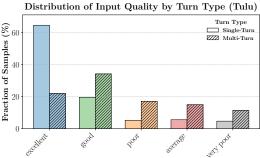
Overall, both Tulu and SmolTalk consist primarily of high-quality instructions, reflecting the use of capable LLMs during data generation and the application of rigorous quality control procedures.

**Tulu.** Fig. 14a shows the overall distribution of input quality labels across all Tulu samples, while Fig. 14b breaks down the distribution by ST and MT samples. In addition, Table 10 reports the supporting statistics. Tulu is predominantly composed of high-quality inputs, with over 80% of samples rated as either "excellent" or "good". This aligns with the strict curation and quality filtering practices described in Lambert et al. [7]. A similar trend holds for ST samples, which make up 95% of the dataset. For MT samples, the distribution is more balanced, with most samples rated as "good", followed by "excellent". However, a non-negligible portion of MT samples (26.5%) fall into the "poor" or "very poor" categories. As discussed in the main paper, this motivates a rigorous quality filtering step when constructing new data mixtures. This is further supported by our later analysis of instruct reward scores, which reveals a clear correlation between poor input quality and poor response quality.

Table 10: Input quality distribution for the Tulu dataset, shown overall and broken down by single-turn (ST) and multi-turn (MT) samples.

Input Quality	Total Count	% of All Samples	ST Sample Count	% of ST Samples	MT Sample Count	% of MT Samples
excellent	572343	62.77%	563307	64.69%	9036	22.06%
good	185502	20.34%	171465	19.69%	14037	34.27%
average	52925	5.80%	45900	5.27%	7025	17.15%
poor	55027	6.04%	48842	5.61%	6185	15.10%
very poor	45985	5.04%	41305	4.74%	4680	11.42%

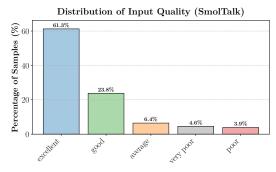


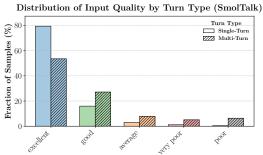


- (a) Overall input quality distribution for Tulu: most ity, indicating rigorous quality controls during curation. samples are of "good" quality, followed by "excellent".
- (b) Input quality distribution by turn type for Tulu: most samples (over 80%) are of "excellent" or "good" qual- ST samples are of "excellent" quality while most MT

Figure 14: Distribution of Magpie input quality labels for Tulu: (a) overall input quality distribution, (b) distribution by turn type (single-turn vs. multi-turn).

**SmolTalk.** Similarly, Fig. 15a shows the overall distribution of input quality labels across all SmolTalk samples and Fig. 15b breaks down the distribution by ST and MT samples, with Table 11 reporting the statistics. SmolTalk also contains predominantly high-quality inputs, with 85% of samples rated as either "excellent" or "good". In contrast to Tulu, significantly fewer samples fall into the "poor" or "very poor" categories, suggesting that Allal et al. [9] applied stricter quality control measures during curation. This trend holds across both ST and MT samples. In particular, the ST subset is even more skewed toward high-quality inputs, with over 95% of ST samples rated as "excellent" or "good". These findings indicate that the SmolTalk data curation process results in consistently high-quality samples, across both turn types.





- most samples (over 85%) are of "excellent" or "good" quality, indicating even stricter quality controls during dataset curation.
- (a) Overall input quality distribution for SmolTalk: (b) Input quality distribution by turn type for SmolTalk: most ST and MT samples are of "excellent" or "good" quality, with significantly smaller portions for "average", "poor", and "very poor".

Figure 15: Distribution of Magpie input quality labels for SmolTalk: (a) overall input quality distribution, (b) distribution by turn type (single-turn vs. multi-turn).

Table 11: Input quality distribution for the SmolTalk dataset, shown overall and broken down by single-turn (ST) and multi-turn (MT) samples.

Input Quality	Total Count	% of All Samples	ST Sample Count	% of ST Samples	MT Sample Count	% of MT Samples
excellent	187 624	61.18%	72 487	79.40%	115 137	53.46%
good	73 108	23.84%	14 370	15.74%	58 738	27.27%
average	19713	6.43%	2 885	3.16%	16 828	7.81%
poor	12 049	3.93%	1 133	1.24%	10916	5.07%
very poor	14 166	4.62%	415	0.45%	13 751	6.38%

### C.4.2 Input Quality by Task Category

In addition to the overall input quality analysis, we examine quality distributions across individual Magpie task categories.

**Tulu.** Table 12 presents the input quality breakdown for each task category, and Fig. 16 visualizes the corresponding fractional shares. *Coding & Debugging* (71.2% "excellent"), *Data Analysis* (79.3% "excellent"), and *Math* (96.0% "excellent") are heavily concentrated in the top quality bin, with negligible low-quality tails. *Editing* (45.1% "good") and *Reasoning* (46.3% "good") skew toward the second-highest bin, yet together still reach close to 80% when combining "excellent" and "good" labels. *Role Playing* (48.2% "excellent"), *Planning* (66.9% "excellent"), and *Creative Writing* (46.1% "excellent") show a more balanced distribution: although they lead in combined "excellent"+"good" ratings, 10–20% of samples fall into "average" or worse. *Advice Seeking* peaks in the "good" category (29.1%) but also has a sizeable lower-quality tail, with 27.9% of samples rated as "poor" or "very poor". *Brainstorming* (26.9% "very poor") and *Others* (41.6% "very poor") exhibit the highest noise levels, with over a quarter of samples rated at the lowest quality tier. These results suggest that open-ended or generative tasks tend to be noisier in Tulu. For downstream modeling and evaluation, filtering to the "excellent"+"good" subset may improve stability and reduce noise. Consequently, we applied a similar strategy in our data mixture curation recipe.

Table 12: Input quality by Magpie task category for Tulu. Each row reports the proportion of samples rated as *excellent*, *good*, *average*, *poor*, or *very poor* within each task category.

Task Category	Excellent	Good	Average	Poor	Very Poor
Advice seeking	26.1	29.1	16.9	20.3	7.6
Brainstorming	24.2	26.8	10.2	11.9	26.9
Coding & Debugging	71.2	21.8	3.6	2.3	1.1
Creative writing	46.1	31.8	10.8	8.0	3.3
Data analysis	79.3	16.3	2.8	1.3	0.4
Editing	35.4	45.1	8.7	7.1	3.8
Information seeking	33.9	36.2	10.6	9.9	9.4
Math	96.0	2.8	0.7	0.4	0.2
Others	5.3	6.4	6.7	40.0	41.6
Planning	66.9	20.0	6.8	4.8	1.6
Reasoning	30.0	46.3	10.4	7.2	6.0
Role playing	48.2	24.8	9.3	9.9	7.7

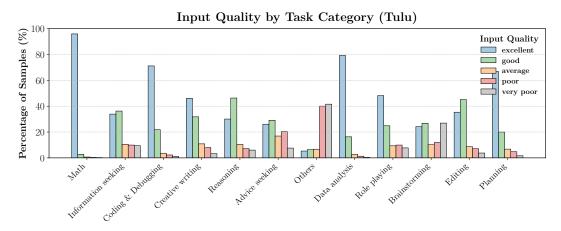


Figure 16: Input quality distribution by Magpie task category for Tulu. STEM-oriented tasks (e.g., *Math*, *Coding*) exhibit predominantly high-quality inputs, while open-ended or generative tasks (e.g., *Brainstorming*, *Advice Seeking*) show greater variability and more frequent low-quality samples.

**SmolTalk.** Table 13 presents the input quality breakdown for each task category, and Fig. 17 visualizes the corresponding fractional shares, Coding & Debugging (81.7% "excellent"), Math (88.2% "excellent"), and Data Analysis / Reasoning (both around 67% "excellent") are heavily concentrated in the top quality bin, with combined "excellent"+"good" shares of 98.0%, 98.0%, and 94.8%, respectively. Editing and Brainstorming peak in the "excellent" bin (39.4% and 51.3%), but also include substantial "good" proportions (33.3% and 28.4%), resulting in a combined "excellent"+"good" share of 70-80%. Creative Writing (44.7% "excellent", 36.3% "good") and Role Playing (61.4% "excellent", 21.0% "good") show greater variability, with 15–20% of samples rated as "average" or worse. Advice Seeking includes 48.3% "excellent" and 28.7% "good", but also a non-negligible "very poor" fraction (12.5%), indicating some noisy or ill-formed queries. Planning shows the largest "very poor" tail (13.6%), while Editing and Information Seeking have the highest combined share of "poor"+"very poor" ratings (17.0%), suggesting these categories include more problematic inputs. Overall, these results indicate that closed-form and structured tasks (e.g., Math, Coding, Data analysis) yield the highest input quality, whereas open-ended or generative tasks remain more prone to noise, even in SmolTalk. As with Tulu, filtering for the combined "excellent"+"good" subset may improve downstream model stability.

Table 13: Input quality percentages by Magpie task category for SmolTalk. Each row reports the proportion of samples rated as *excellent*, *good*, *average*, *poor*, or *very poor* within each task category.

Task Category	Excellent	Good	Average	Poor	Very Poor
Advice seeking	48.3	28.7	7.5	3.0	12.5
Brainstorming	51.3	28.4	9.8	3.7	6.8
Coding & Debugging	81.7	16.4	1.4	0.4	0.1
Creative writing	44.7	36.3	16.1	2.3	0.6
Data analysis	66.6	28.0	4.3	0.8	0.3
Editing	39.4	33.3	10.3	13.2	3.8
Information seeking	43.4	31.2	8.7	6.1	10.6
Math	88.2	9.9	1.2	0.5	0.2
Others	56.3	29.9	6.6	2.4	4.9
Planning	43.8	26.8	11.6	4.3	13.6
Reasoning	67.0	25.2	4.6	2.1	1.1
Role playing	61.4	21.0	7.8	7.4	2.4

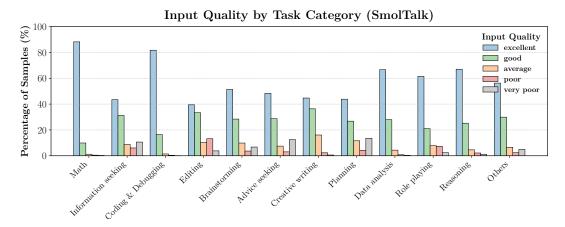


Figure 17: Input quality distribution by Magpie task category for SmolTalk. STEM-oriented tasks (e.g., *Math*, *Coding*) exhibit predominantly high-quality inputs, while open-ended or generative tasks (e.g., *Brainstorming*, *Advice Seeking*) show greater variability and more frequent low-quality samples.

### **C.5** Response Quality Analysis

Magpie rates the response quality, i.e., the quality of the assistant's response to a user prompt, as the *instruct reward* via a language model-based reward model. Specifically, it employs *FsfairX-LLaMA3-RM-v0.1* [70–72], a Llama-3-8B-Instruct-based reward model that assigns a continuous-valued score to each response. Since the original implementation supports only single-turn conversations, we extend the reward annotation pipeline to handle multi-turn samples by using a separate Llama-3.3-70B-Instruct-based LLM-as-a-Judge to evaluate MT responses on a scale between 0-5. We refer to more details in App. C.

### C.5.1 Single-Turn Reward Distributions

**Tulu.** Fig. 18 shows the distribution of instruct reward scores by task category for Tulu's ST samples. The distribution is roughly bell-shaped, with most scores falling in the range of [-6, +6] and a peak density between +1 and +2. Notably, *Math* and *Coding & Debugging* receive almost exclusively non-negative scores, peaking around +1 to +3, reflecting clear, well-structured prompts with high response quality. *Information Seeking*, *Reasoning*, and *Data Analysis* are centered closer to zero, with modest tails extending into negative reward regions. In contrast, *Advice Seeking*, *Brainstorming*, *Creative Writing*, and *Others* exhibit heavy left tails (extending to -12), indicating many low-quality or poorly answered prompts. These observations suggest that filtering samples by a reward threshold (e.g.,  $\geq 0$  or  $\geq 1$ ) may yield a cleaner, high-quality single-turn subset dominated by *Math* and *Coding* tasks, while low-reward examples (e.g.,  $\leq -3$ ) can help identify problematic, open-ended prompts for further curation. We directly incorporate these insights into our dataset curation recipe (see App. D).

### Single-Turn Instruct Reward Distribution by Task Category (Tulu)

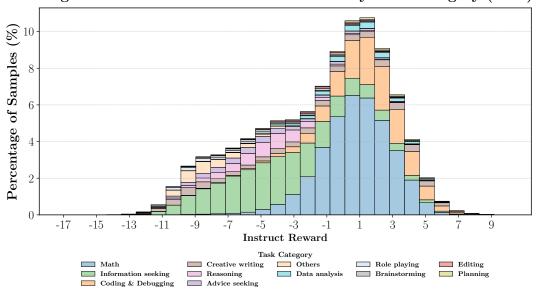


Figure 18: Distribution of single-turn instruct reward scores in the Tulu dataset, broken down by Magpie task category. STEM-oriented tasks (e.g., *Math*, *Coding & Debugging*) receive predominantly non-negative scores, reflecting high-quality, well-answered prompts. In contrast, open-ended and creative tasks (e.g., *Creative Writing*, *Advice Seeking*) exhibit heavier negative tails, indicating a higher prevalence of low-quality or poorly answered examples.

**SmolTalk.** Fig. 19 shows the distribution of instruct reward scores by task category for SmolTalk's ST samples. The distribution is approximately bell-shaped, spanning the range [-9, +7], with the highest density around +1. *Coding & Debugging* receives almost exclusively non-negative scores, peaking between +1 and +3, indicating well-posed prompts that the model handles reliably. *Math* is more evenly distributed around zero, suggesting greater variation in prompt clarity or complexity. *Information Seeking*, *Reasoning*, and *Data Analysis* are similarly centered near zero, with modest negative tails extending to -5, reflecting mixed response quality across these domains. *Advice Seeking*, *Brainstorming*, *Creative Writing*, and *Others* exhibit heavier left tails reaching down to -7, suggesting a greater fraction of underspecified or incoherent prompts. These trends again suggest that filtering samples by reward thresholds (e.g.,  $\geq 0$  or  $\geq 1$ ) can yield a high-quality subset dominated by *Math* and *Coding* tasks, while low-reward samples (e.g.,  $\leq -3$ ) highlight problematic open-ended prompts that may benefit from further curation. We elaborate on these filtering strategies in App. D.

### Instruct Reward Distribution by Task Category (SmolTalk) Percentage of Samples (%)4 2 -17 -15 -13 -11 -9 -5 -3 -1 3 Instruct Reward Task Category Math Editing Advice seeking Reasoning Planning Role playing Coding & Debugging Brainstorming

Figure 19: Distribution of single-turn instruct reward scores in the SmolTalk dataset, broken down by Magpie task category. STEM-oriented tasks (e.g., *Math*, *Coding & Debugging*) receive predominantly non-negative scores, indicating reliable and well-structured prompts. Open-ended and creative tasks (e.g., *Creative Writing*, *Advice Seeking*) exhibit similar distributions with slightly broader negative tails, suggesting a slightly higher prevalence of underspecified or incoherent prompts.

Creative writing

Information seeking

#### C.5.2 Multi-Turn Reward Distributions

**Tulu.** Fig. 20 shows the distribution of instruct reward scores by task category for Tulu's MT samples. Nearly 90% of MT samples receive the maximum reward score of 5, approximately 8% land at 4, and the remaining 2% are scattered across scores 0–3. *Information Seeking* alone accounts for roughly 35% of the reward-5 bin, followed by *Creative Writing* at around 15% and *Coding & Debugging* at 12–13%. All other categories (e.g., *Advice Seeking, Role Playing, Math*) each contribute between 2–8% of that top bin. The ∼8% of samples rated at reward 4 exhibit a similar task distribution, with *Information Seeking, Coding & Debugging*, and *Creative Writing* again leading, though categories such as *Advice Seeking* and *Role Playing* are relatively over-represented compared to the reward-5 group. Scores ≤ 3 are vanishingly rare. When they do occur, they disproportionately stem from open-ended categories such as *Advice Seeking, Creative Writing*, and *Role Playing*, likely reflecting occasional multi-turn drift or incoherence. These observations indicate that MT conversations are overwhelmingly rated "*excellent*" by the reward model, especially for structured tasks like *Information Seeking, Coding*, and *Math*. Creative and advisory interactions, while still high-quality on average, account for the largest share of samples in the reward-4 bin and the only non-zero mass below 4, suggesting that these task types may benefit from additional filtering.

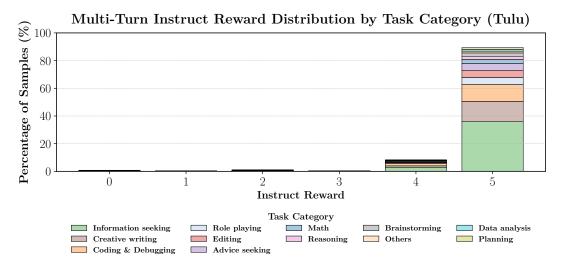


Figure 20: Distribution of multi-turn instruct reward scores in the Tulu dataset, broken down by Magpie task category. The vast majority of samples receive the maximum score of 5, with structured tasks such as *Information Seeking*, *Coding & Debugging*, and *Math* dominating this top bin. Creative and open-ended tasks (e.g., *Creative Writing*, *Advice Seeking*, *Role Playing*) are over-represented in the small mass at score 4 and account for nearly all samples scoring below 4, highlighting them as key targets for further quality filtering.

**SmolTalk.** Fig. 21 shows the distribution of instruct reward scores by task category for SmolTalk's MT samples. As with Tulu, nearly 90% of MT samples receive the maximum reward score of 5, approximately 8% score 4, and the remaining 2% fall into bins 0–3. *Information Seeking* contributes the largest share, accounting for roughly 22–23% of the reward-5 bin. Editing follows with around 14%, and Math with approximately 10%. Advice Seeking, Coding & Debugging, and Brainstorming each make up about 8-9%. Creative Writing, Planning, and Data Analysis contribute mid-single-digit proportions (5–7%), while Reasoning and Role Playing round out the top bin with around 4–5% each. The samples scoring 4 (roughly 8% of total) broadly mirror the top-bin rankings, though open-ended tasks such as Advice Seeking and Creative Writing are slightly more prominent. Scores  $\leq 3$  are extremely rare (fewer than 2% overall), and when present, are disproportionately drawn from open-ended categories such as Advice Seeking, Creative Writing, and Role Playing, smilarly reflecting occasional context drift or incoherence. These findings indicate that MT conversations in SmolTalk, as in Tulu, are overwhelmingly rated "excellent" by the reward model, particularly for structured tasks such as Information Seeking and Math. Open-ended interactions, while still achieving high scores on average, represent the only meaningful mass below 4, suggesting these categories may benefit from further quality filtering as well.

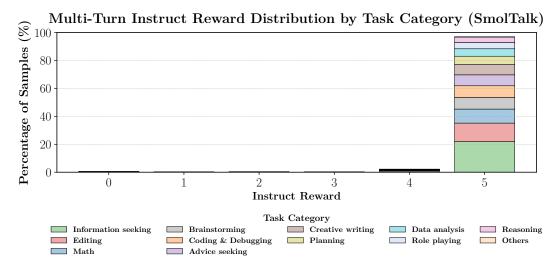


Figure 21: Distribution of multi-turn instruct reward scores in the SmolTalk dataset, broken down by Magpie task category. Most samples receive the maximum score of 5, with structured tasks such as *Information Seeking* and *Math*, but also *Editing* dominating the top bin. Open-ended tasks (e.g., *Advice Seeking, Creative Writing, Role Playing*) contribute more substantially to lower reward scores, including the small but non-zero mass in the 0–3 range, suggesting they may benefit from further curation or quality filtering.

### C.5.3 Instruct Reward vs. Input Quality

In this section, we investigate the relationship between input quality and instruct reward to validate the intuition that poorly formulated user prompts often lead to suboptimal assistant responses.

**Single-Turn Case.** Fig. 22 and Fig. 23 show the distribution of single-turn reward scores across task categories, grouped by input quality label, for both Tulu and SmolTalk datasets. In general, single-turn instruct rewards exhibit a strong correlation with input quality. *Excellent* prompts yield reward scores mostly in the +1 to +5 range, peaking around +2. *Good* prompts are centered between -5 and +1. *Average* inputs result in rewards concentrated around -7 to -3, while *Very Poor* prompts are heavily skewed toward -11 to -7. These patterns confirm that input quality is a strong predictor of response quality for the majority of single-turn samples for both datasets.

**Multi-Turn Case.** Fig. 24 and Fig. 25 show the distribution of multi-turn reward scores across task categories, grouped by input quality label, for both Tulu and SmolTalk datasets. While single-turn rewards provide a clear, continuous signal of prompt quality, multi-turn reward scores are heavily saturated at the maximum value (5) for both Tulu and SmolTalk, resulting in a loss of discriminative power across input quality strata. A closer inspection of our annotated data samples reveals why this occurs. Below are two illustrative cases where the input quality is rated as "*poor*", yet the overall multi-turn conversation still receives a perfect instruct reward of 5.

## Example 1: Assistant starts first and initial prompt has typos.

In this example, two factors contribute to the low input quality rating: (1) The conversation begins with the assistant rather than the user, due to the inclusion of a system-style prompt, something that the Magpie input-quality rater penalizes. (2) The initial prompt includes a typo ("*Jhonny*" instead of "*Johnny*"), which also contributes to a lower input quality score. Despite these, the assistant's behavior remains consistent and coherent, resulting in a perfect reward by imitating Johnny Bravo.

### Example 2: Vague user query is clarified later.

In this case, the first user input is vague and could improve from better grammar, leading to a low input quality rating by Magpie. However, the user clarifies their request in the following turns. The assistant responds appropriately and in detail, producing a coherent and informative answer by the end of the conversation. This illustrates how multi-turn interactions can recover from poor initial queries, yielding high-quality final responses despite the low initial rating.

Together, these examples highlight a key distinction: multi-turn conversations may achieve high reward scores even when the initial input is of poor quality, particularly when clarification or intent refinement occurs across turns. As a result, input quality is less predictive of instruct reward in the multi-turn case than in the single-turn setting. This observation initially motivated the development of a dedicated multi-turn annotation pipeline for Magpie, ensuring that reward labels reflect the quality of the entire conversation rather than just the initial prompt.

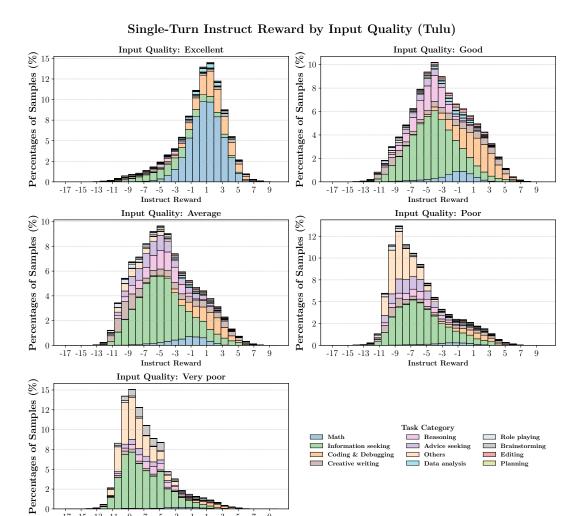


Figure 22: Distribution of single-turn instruct reward scores by input quality label in the Tulu dataset. Higher-quality prompts (*excellent*, *good*) correspond to significantly higher reward scores, while lower-quality inputs (*average*, *poor*, *very poor*) are associated with markedly lower rewards. This confirms a strong correlation between input quality and response quality in the single-turn setting.

-17 -15 -13 -11 -9

-7 -5 -3 -1 Instruct Reward

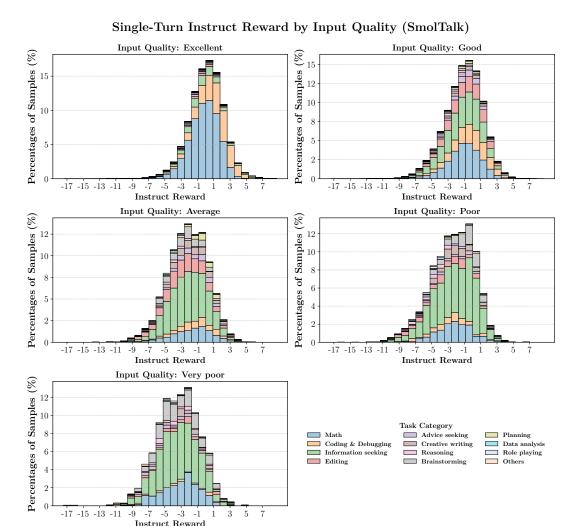


Figure 23: Distribution of single-turn instruct reward scores by input quality label in the SmolTalk dataset. As with Tulu, higher input quality is strongly correlated with higher instruct reward, demonstrating that prompt clarity and specificity are key drivers of response quality in the single-turn setting.

# Multi-Turn Instruct Reward by Input Quality (Tulu) Input Quality: Excellent Input Quality: Good Percentages of Samples (%) Percentages of Samples (%) 20 0 3 5 2 3 Instruct Reward 5 Input Quality: Average Input Quality: Poor Percentages of Samples (%) $^{00}$ $^{00}$ $^{00}$ $^{00}$ $^{00}$ Percentages of Samples (%) 20 0 2 3 5 ò 2 3 5 Input Quality: Very poor Percentages of Samples (%)

Figure 24: Distribution of multi-turn instruct reward scores by input quality label in the Tulu dataset. Most samples, regardless of input quality, receive the maximum reward score of 5, suggesting that clarification across turns often compensates for initially vague or low-quality prompts.

2 3 Instruct Reward

Task Category

Information seeking

Creative writing

Coding & Debugging

Role playing

Editing
Advice seeking

ory
Math
Reasoning
Brainstorn
Others

Data analysis
Planning

### Multi-Turn Instruct Reward by Input Quality (SmolTalk) Input Quality: Excellent Input Quality: Good 20 Ó 2 5 2 5 3 3 4 Instruct Reward Input Quality: Average Input Quality: Very poor Percentages of Samples (%) $^{100}$ $^{00}$ $^{00}$ $^{00}$ $^{00}$ $^{00}$ Percentages of Samples (%) 80 60 40 20 Ó 3 5 2 3 5 Input Quality: Poor Percentages of Samples (%) $\begin{array}{ccc} 000 & 000 \\ 00 & 00 \\ \end{array}$ Task Category Creative Planning Data analysis Information Editing Math 60 Brainstorming Coding & Debugging Advice seeking Reasoning Others

Figure 25: Distribution of multi-turn instruct reward scores by input quality label in the SmolTalk dataset. Similar to Tulu, the reward model heavily favors MT conversations with perfect scores, even for lower-rated prompts, reflecting the tendency of multi-turn dialogues to recover from poor initial queries through user clarification.

2 3 Instruct Reward

### C.6 Difficulty Analysis

In this section, we analyze how Magpie's difficulty labels are distributed across task categories for the Tulu and SmolTalk datasets. We include both overall and turn-type-specific analyses.

### C.6.1 Overall Distribution

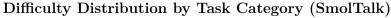
Fig. 26 and Fig. 27 show the relative difficulty distribution per task category for Tulu and SmolTalk. Each bar reflects the percentage of a task's samples that fall into each difficulty bin.

**Tulu.** *Math* dominates the *easy*, *hard*, and *very hard* bins, accounting for 45%, 37%, and 36% of the samples in those categories, respectively. *Information Seeking* peaks at *very easy* (44%), and remains substantial in both *easy* (28%) and *medium* (32%). *Coding & Debugging* is spread across all difficulty levels: approximately 17% in *easy*, 22% in *medium*, 12% in *hard*, and 14% in *very hard*. It is broadly represented but does not dominate any particular bin. Other categories, including *Creative Writing*, *Role Playing*, and *Advice Seeking*, each account for no more than 10% of any difficulty bin. This distribution suggests that fact-based tasks (e.g., *Math*, *Information Seeking*, *Coding*) dominate mid-to-lower difficulty levels, while creative and advisory tasks remain relatively underrepresented across all levels.

**SmolTalk.** *Math* similarly dominates the *hard* and *very hard* bins, contributing approximately 28% and 47% of the samples, respectively. *Information Seeking* peaks at *very easy* (35%) and remains substantial in *easy* (25%), while being evenly represented across other bins as well. *Coding & Debugging* is fairly balanced across difficulty levels, showing no strong concentration at either extreme. All other task categories, including *Creative Writing*, *Role Playing*, and *Advice Seeking*, remain minor contributors with  $\leq$ 10% in any bin. These patterns suggest that again fact-based tasks, especially *Math*, skew toward mid-to-high difficulty, whereas creative and advisory tasks occur infrequently and are less likely to be rated as difficult.

# Difficulty Distribution by Task Category (Tulu) Percentage of Samples (%)30 20 very hard very easy medium hard easy Task Category Editing Creative writing Others Role playing Information seeking Reasoning Data analysis Coding & Debugging Advice seeking

Figure 26: Distribution of difficulty ratings by task category for Tulu. Each bar shows the relative difficulty composition within a task.



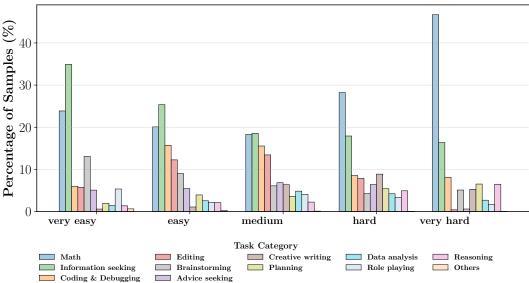


Figure 27: Distribution of difficulty ratings by task category for SmolTalk. Each bar shows the relative difficulty composition within a task.

### C.6.2 Single-Turn

Fig. 28 and Fig. 29 show the relative difficulty distribution per task category for single-turn samples in Tulu and SmolTalk. Each bar reflects the percentage of a task's single-turn samples that fall into each difficulty bin.

**Tulu.** In the single-turn setting, *Math* continues to dominate the *easy* (approximately 46%) and *hard* (38%) bins, while *Information Seeking* peaks in the *very easy* bin (44%) and also contributes around 13% to *very hard. Coding & Debugging* is distributed across *easy* (18%), *medium* (22%), and *hard* (12%), maintaining a consistent presence across difficulty levels. *Creative Writing* and *Role Playing* remain underrepresented in the lower difficulty bins but rise to 10–12% in the *very hard* bin. Given Tulu's predominantly single-turn nature, it is unsurprising that fact-based tasks dominate the lower difficulty levels, while creative and open-ended tasks contribute disproportionately to the hardest examples.

**SmolTalk.** In SmolTalk, *Math* shows strong representation across all difficulty levels, from *very easy* to *very hard*, highlighting its prominence in single-turn problem—solution prompts. *Coding & Debugging* is also evenly distributed across the difficulty bins, showing no strong skew. Other categories such as *Information Seeking* and *Editing* appear broadly stratified as well, without any pronounced concentration, suggesting a relatively uniform difficulty distribution across task types.

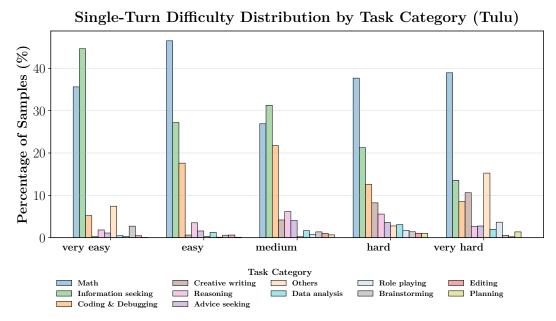


Figure 28: Difficulty distribution by task category for single-turn samples in Tulu. Each bar shows the relative proportion of difficulty labels within each task. Fact-based tasks dominate lower difficulty levels, while creative and role-based prompts appear more frequently in the hardest bins.

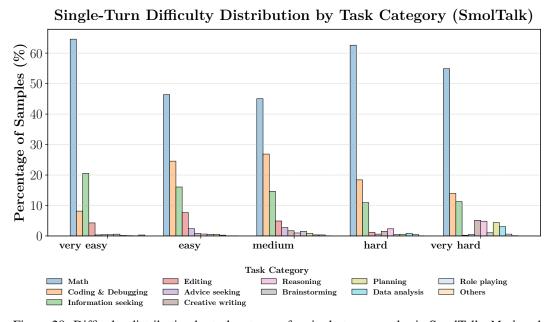


Figure 29: Difficulty distribution by task category for single-turn samples in SmolTalk. *Math* and *Coding & Debugging* are consistently present across all difficulty bins, while other task types remain evenly stratified with no strong concentration.

#### C.6.3 Multi-Turn

Fig. 30 and Fig. 31 show the relative difficulty distribution per task category for multi-turn samples in Tulu and SmolTalk. Each bar reflects the percentage of a task's multi-turn samples that fall into each difficulty bin.

**Tulu.** In the multi-turn setting, *Information Seeking* becomes even more dominant, comprising approximately 53% of *easy*, 47% of *medium*, and 48% of *very easy* samples. *Coding & Debugging* and *Math* together account for 25–35% of samples across all difficulty bins, with *Math* slightly more prevalent in the *hard* and *very hard* categories. *Creative Writing* and *Role Playing* each contribute around 18% to the *very hard* bin, indicating that these open-ended multi-turn dialogues pose significant challenges. Overall, multi-turn conversations in Tulu are heavily concentrated on information-seeking tasks, while creative and role-based categories contribute more prominently to the high-difficulty tail than in the single-turn or overall distributions.

**SmolTalk.** Information Seeking is again highly prevalent, contributing approximately 43% of very easy, 30% of easy, and 24% of very hard multi-turn samples. Math continues to dominate the very hard category. Coding & Debugging is evenly distributed across the lower difficulty bins (very easy to hard), but has almost no presence in the very hard bin. Brainstorming is fairly evenly represented across all difficulty levels, likely due to its inherently interactive and exploratory nature in multi-turn settings. Overall, SmolTalk's multi-turn conversations remain focused on fact-based tasks, especially Math, while open-ended tasks contribute more sparsely and with a wider difficulty spread.

# Multi-Turn Difficulty Distribution by Task Category (Tulu)

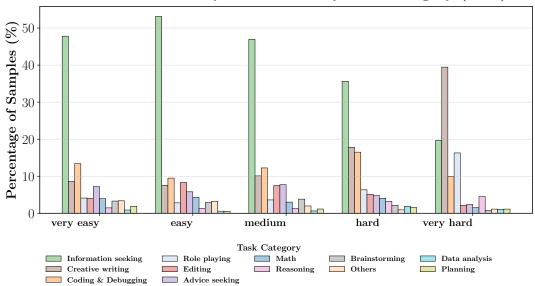


Figure 30: Difficulty distribution by task category for multi-turn samples in Tulu. *Information Seeking* dominates the easier bins, while open-ended tasks such as *Creative Writing* and *Role Playing* contribute substantially to the *very hard* bin.

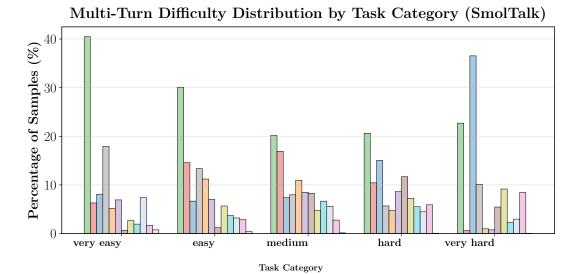


Figure 31: Difficulty distribution by task category for multi-turn samples in SmolTalk. *Math* and *Information Seeking* are prominent across all bins, while categories like *Brainstorming* and *Coding & Debugging* are more evenly spread across difficulty levels.

Creative writing

Planning

Data analysis

Role playing

Reasoning

Others

#### C.6.4 Instruction Reward vs. Difficulty

Brainstorming

Advice seeking

Coding & Debugging

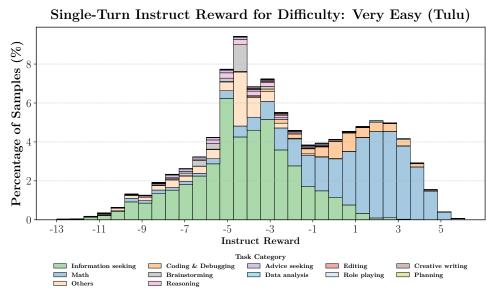
Information seeking

Editing

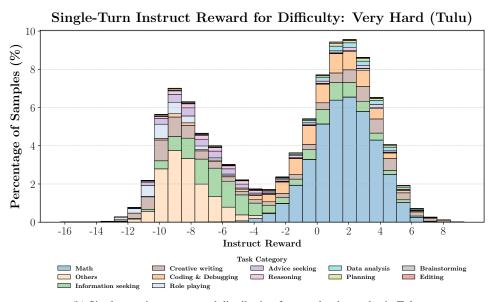
To assess the relationship between task difficulty and response quality, Fig. 32, Fig. 33, Fig. 34, and Fig. 35 show instruct reward distributions for single-turn and multi-turn samples in the Tulu and SmolTalk datasets, respectively. Overall, we observe that difficulty has only a negligible effect on reward distribution, altering the spread and shape only marginally. As such, we do not consider difficulty a key optimization lever in our dataset curation recipe.

**Tulu.** For Tulu, the instruct reward distribution remains largely stable across difficulty levels in both single-turn and multi-turn settings. In the single-turn case, the overall reward distribution is consistent across difficulties, ranging from approximately –14 to +7, with only slightly clearer separation between low- and high-reward samples in the *very hard* bin (see Fig. 32b). In the multi-turn case, the reward values themselves remain unchanged and only the distribution of task categories within difficulty bins varies slightly (see Fig. 33a and Fig. 33b). Thus, unlike input quality, difficulty shows minimal predictive power over response quality for Tulu.

**SmolTalk.** Similarly, for SmolTalk, the reward distributions are largely invariant to difficulty levels. In the single-turn case, the overall reward range stays consistent, though for very hard samples, the peak shifts slightly from around +1 to 0 (see Fig. 34a and Fig. 34b). In the multi-turn case, as with Tulu, reward scores remain constant, with changes only in the composition of underlying task categories (see Fig. 35a and Fig. 35b). In summary, difficulty annotations do not significantly impact the reward model's output, and thus play only a minor role in shaping response quality in SmolTalk.

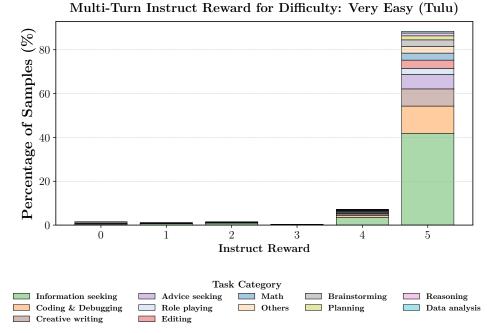


(a) Single-turn instruct reward distribution for very easy samples in Tulu.



(b) Single-turn instruct reward distribution for very hard samples in Tulu.

Figure 32: Instruct reward distribution by difficulty level for single-turn samples in Tulu. The overall shape remains consistent, with slightly clearer separation of low and high rewards in very hard samples.



(a) Multi-turn instruct reward distribution for very easy samples in Tulu.

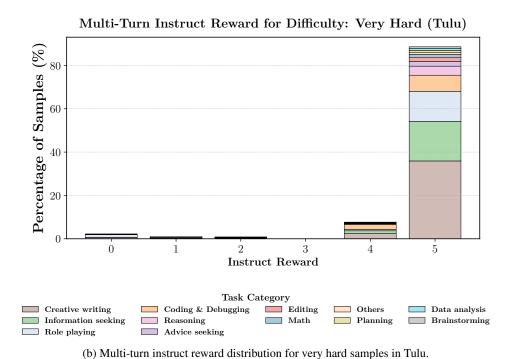
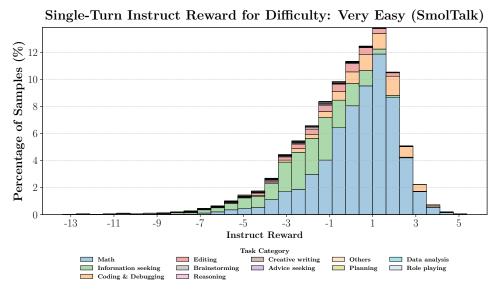
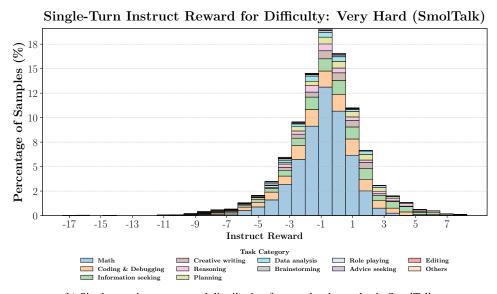


Figure 33: Instruct reward distribution by difficulty level for multi-turn samples in Tulu. Reward values remain saturated at 5 and only task composition within bins changes.

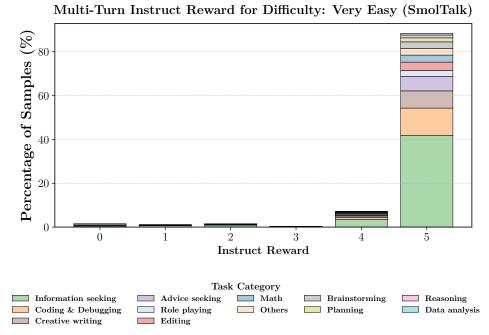


(a) Single-turn instruct reward distribution for very easy samples in SmolTalk.



 $(b) \ Single-turn \ instruct \ reward \ distribution \ for \ very \ hard \ samples \ in \ Smol Talk.$ 

Figure 34: Instruct reward distribution by difficulty level for single-turn samples in SmolTalk. Reward ranges remain stable, with a slight leftward shift for very hard prompts.



(a) Multi-turn instruct reward distribution for very easy samples in SmolTalk.

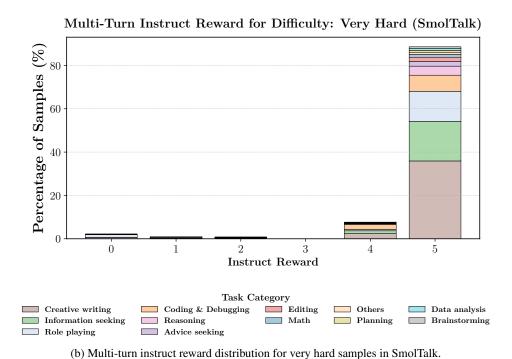


Figure 35: Instruct reward distribution by difficulty level for multi-turn samples in SmolTalk. Reward saturation at score 5 persists across difficulty levels, with only minor shifts in task composition.

### C.7 Language Analysis

In this section, we provide an overview of the language distribution in the Tulu and SmolTalk datasets.

## C.7.1 Overall Language Distributions

Both Tulu and SmolTalk are predominantly English datasets. Fig. 36a shows the top five languages represented in Tulu, with English (EN) accounting for 95.4% of all samples, followed by Russian (RU) at 1.5% and Simplified Chinese (ZH) at 1.1%. Fig. 36b presents the same analysis for SmolTalk, where English dominates even more strongly, comprising 99.3% of all samples. These results indicate that both datasets are almost exclusively focused on English conversations, with only marginal inclusion of multilingual content.

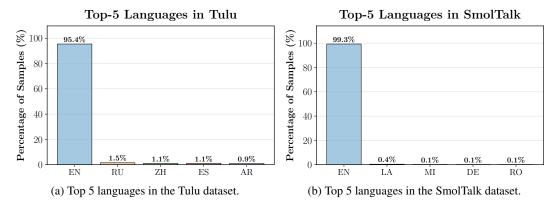


Figure 36: Overall language distribution in the Tulu and SmolTalk datasets. Both are overwhelmingly English-centric, with only a small fraction of samples in other languages such as Russian and Chinese.

# C.7.2 Language by Task Category

Fig. 37 Fig. 38 show the top three languages by task category for the Tulu and SmolTalk datasets.

For Tulu, *Math* accounts for the largest share of English samples (42%), followed by *Information Seeking* and *Coding*, each contributing around 17%. Russian and Chinese samples are predominantly associated with *Information Seeking* tasks, an intuitive result, as users often query factual information in their native language during chat interactions.

In SmolTalk, the distribution of English samples is more balanced, with *Math* and *Information Seeking* comprising 22% and 20%, respectively. Interestingly, in the Latin American language group (LA), the vast majority of samples (75%) correspond to *Math* tasks. Upon inspection, we find that many of these are simple mathematical expressions, e.g., "24 x 17 + 673 - 36.7 = ?", containing no natural language text. Magpie does not misclassify these samples per se, but rather assigns them to the LA language group, likely due to a lack of sufficient linguistic signal to support a more accurate classification. While this behavior is notable, the overall size of the LA subset is only 0.4% of the dataset, making this an inconsequential artifact in practice.

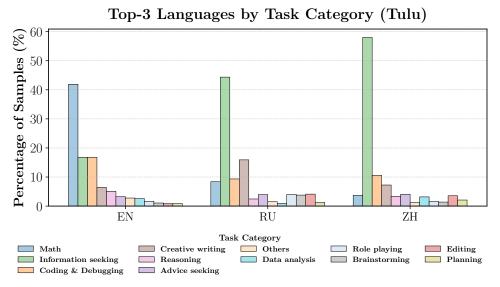


Figure 37: Top 3 languages by task category for the Tulu dataset. English samples are dominated by *Math*, *Information Seeking*, and *Coding*, while Russian and Chinese samples primarily cluster around *Information seeking* queries.

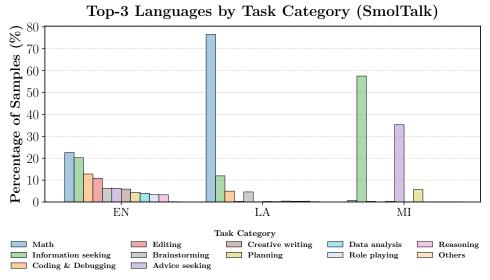


Figure 38: Top 3 languages by task category for the SmolTalk dataset. English samples are largely split between *Math* and *Information Seeking*. Latin American samples are mostly simple mathematical expressions, leading to their classification under *Math* despite minimal linguistic content.

#### C.8 Safety

Safety is a crucial aspect of post-training datasets. In this section, we examine the safety characteristics of the Tulu and SmolTalk corpora.

### **C.8.1** Overall Safety Distribution

Fig. 39 shows the overall safety distribution for the Tulu and SmolTalk datasets. In general, both datasets are predominantly safe, with 97.4% of Tulu samples and 99.1% of SmolTalk samples flagged as safe. This reflects the rigorous quality control applied by Lambert et al. [7] and Allal et al. [9], which includes an explicit focus on safety during data collection and filtering. Nevertheless, a small fraction of samples are labeled as unsafe. Below, we provide two representative examples from Tulu and SmolTalk.

# 

Figure 39: Safety distribution for Tulu and SmolTalk. Both datasets are predominantly safe.

### Example 1 from Tulu: Medical advice.

In this example, the assistant provides *specialized advice*, which is flagged by Llama-Guard 2 [29] as inappropriate, particularly due to its medical context. Even if the content appears benign or well-intentioned, Llama-Guard still classifies it under one of its 11 unsafe categories.

#### Example 2 from SmolTalk: Casino game.

In this case, the user is asking for technical guidance on building a casino-style game. Although the query and response are not overtly harmful, Llama-Guard flags the conversation as unsafe due to its association with gambling, assigning it to the *non-violent crime* category.

These examples illustrate that most unsafe samples are benign in appearance but contain elements, such as medical or gambling-related content that trigger conservative safety filters. Nonetheless, the proportion of such flagged instances is negligible in both datasets. However, safety in LLM fine-tuning remains an active area of research [73], with various mechanisms available to instill safety both during and after training [74–76]. We leave a more comprehensive safety analysis of post-training datasets to future work.

# C.8.2 Safety by Task Category

Fig. 40 and Fig. 41 show the distribution of safe and unsafe samples across task categories in the Tulu and SmolTalk datasets.

Overall, both datasets exhibit no meaningful concentration of unsafe samples in any specific task category. In SmolTalk, for example, the highest proportion of unsafe samples appears in *Information Seeking*, but even here the rate remains extremely low at just 2.6%. This analysis supports our earlier observations: unsafe labels are rare, broadly and uniformly distributed, and not linked to any anomalous or harmful behavior within specific task types. Instead, most flagged cases reflect conservative or overly sensitive filtering (see previous examples). As such, the safety risks at the task-category level are negligible and likely represent noise or edge-case overflagging by Magpie's Llama Guard safety classifier.

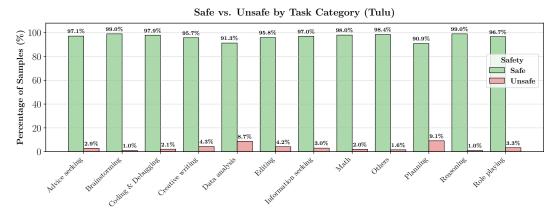


Figure 40: Distribution of safe and unsafe samples by task category in the Tulu dataset. Unsafe samples are rare and show no meaningful concentration in any specific category.

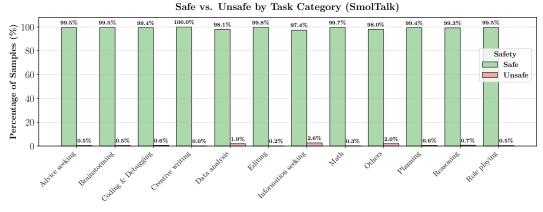


Figure 41: Distribution of safe and unsafe samples by task category in the SmolTalk dataset. Unsafe samples are rare and show no meaningful concentration in any specific category.

# **D** Data Curation Recipe Details

This section provides a detailed overview of our quality-based and task-aware data curation recipe used to construct our *TuluTalk* data mixture. The steps of the algorithm are outlined in Fig. 42.

In **Step 1**, we compute quantiles over reward scores to guide subsequent selection thresholds. Specifically, we compute:

- · First and second quantiles of single-turn samples with input quality labeled as excellent
- Third quantile of single-turn samples with input quality good

These thresholds serve as principled cutoffs for isolating top-tier completions, allowing us to distinguish high-reward responses from more average ones within higher-quality prompt strata.

**Step 2** constitutes our initial quality-based curation stage. Here, we select only samples with the highest input quality and highest response reward. This includes all multi-turn samples labeled excellent with a reward score of 5, and all single-turn samples labeled excellent with a reward score above the second quantile.

Step 3 identifies task categories whose representation in the selected set  $\mathcal{D}_c$  drops by more than a threshold  $\tau$  relative to the original dataset. This step ensures that quality filtering does not disproportionately exclude certain task types.

In **Step 4**, we reintroduce high-quality fallback samples from underrepresented task categories to restore diversity. Specifically, we add:

- Multi-turn samples with input quality excellent and response reward of 4
- Single-turn samples with input quality excellent and response reward between the first and second quantiles

These samples are labeled as "high-quality fallback" in Fig. 42.

We further boost task diversity by introducing "diversity boost" samples. Specifically, these are:

- Multi-turn samples with input quality good and response reward of 5
- Single-turn samples with input quality good and reward above the third quantile

As discussed in the main paper, we found that applying only the quality-based filtering initially led to suboptimal performance due to a shortage of instruction following samples, an issue successfully addressed by the diversity-enhancing additions in Step 4.

Together, these refinements ensure that the curated dataset maintains both high overall quality and balanced coverage across task categories.

We apply this curation pipeline independently to the annotated Tulu and SmolTalk datasets and merge the resulting subsets to form our *TuluTalk* mixture.

We select the quantiles as an intuitive and natural choice for the thresholds on single-turn reward scores, and do not perform additional ablations due to limited compute budget. We leave a thorough ablation study to find optimum thresholds as a future work.

#### **Quality- and Task-Aware Data Curation Recipe**

**Input:** Annotated dataset  $\mathcal{D}$  with Magpie tags for input quality (input\_quality), single-turn/multi-turn response quality (st\_reward/mt\_reward), and task category (task\_category); task diversity threshold  $\tau$ .

**Output:** Curated subset  $\mathcal{D}_c$  that is both high-quality and task-diverse.

## Recipe:

1. Compute quantiles:

$$\begin{split} Q_1^e,\ Q_2^e \leftarrow 1 \text{st/2nd quantiles of } \big\{ S[\text{st\_reward}] \mid S[\text{input\_quality}] = \text{excellent}, \\ S[\text{turn}] = \text{single\_turn} \big\}, \\ Q_3^g \leftarrow 3 \text{rd quantile of } \big\{ S[\text{st\_reward}] \mid S[\text{input\_quality}] = \text{good}, \\ S[\text{turn}] = \text{single\_turn} \big\}. \end{split}$$

2. For each  $S \in \mathcal{D}$ , add S to  $\mathcal{D}_c$  if

$$\begin{split} S[\texttt{input\_quality}] &= \texttt{excellent} \land \\ \Big( (S[\texttt{turn}] = \texttt{multi\_turn} \land S[\texttt{mt\_reward}] = 5) \\ &\lor (S[\texttt{turn}] = \texttt{single\_turn} \land S[\texttt{st\_reward}] > Q_2^e) \Big). \end{split}$$

- 3. Let C be the set of task categories whose coverage in  $D_c$  drops by more than  $\tau$ % relative to D.
- 4. For each  $S \in \mathcal{D} \setminus \mathcal{D}_c$ , add S to  $\mathcal{D}_c$  if

$$S[\texttt{task\_category}] \in \mathcal{C} \land \\ \left(S[\texttt{input\_quality}] = \texttt{excellent} \land \left( (S[\texttt{turn}] = \texttt{multi\_turn} \land S[\texttt{mt\_reward}] = 4) \right. \\ \left. \qquad \qquad \qquad \lor \left( S[\texttt{turn}] = \texttt{single\_turn} \land Q_1^e < S[\texttt{st\_reward}] < Q_2^e \right) \right) \\ \\ \left. \qquad \qquad \qquad \qquad \qquad \\ \left( S[\texttt{input\_quality}] = \texttt{good} \land \left( (S[\texttt{turn}] = \texttt{multi\_turn} \land S[\texttt{mt\_reward}] = 5) \right. \\ \\ \left. \qquad \qquad \lor \left( S[\texttt{turn}] = \texttt{single\_turn} \land S[\texttt{st\_reward}] > Q_3^g \right) \right) \right) \right) \\$$

Figure 42: Quality- and task-aware curation recipe used to construct the *TuluTalk* data mixture. Steps 1-4 sequentially select high-quality examples (Step 2), identify underrepresented task categories (Step 3), and reintroduce fallback samples (Step 4) to restore task diversity without compromising input or output quality.

diversity boost

# E Details on Experimental Setup and Additional Results

This section presents supplementary results, including those from SFT and DPO, and provides details on the fine-tuning and evaluation configurations used throughout our experiments.

### **E.1** Fine-Tuning Configurations

To ensure reproducibility and comparability, we fine-tune all models using AllenAI's *Open-Instruct* framework<sup>9</sup>, covering both SFT and DPO. By default, Open-Instruct applies a sum-reduction over token-level losses, rather than the more commonly used mean-reduction. This design choice ensures length-equitable weighting, where short and long sequences contribute proportionally to the total loss, preventing shorter examples from disproportionately influencing the gradient due to having fewer tokens. Moreover, summing losses leads to more stable optimization by avoiding fluctuations in loss scale caused by variation in batch composition or sequence length distributions. We refer to a more detailed analysis and discussion in [7].

### **E.1.1** Supervised Fine-Tuning (SFT)

We fine-tune Llama-3.1-8B [27] and SmolLM2-1.7B [9] models on the Tulu [7], SmolTalk [9], Orca [16], and our proposed *TuluTalk* dataset. These two models are selected for consistency with prior work, being the default backbones in the respective dataset papers for Tulu and SmolTalk.

Fine-tuning is performed using BF16 mixed precision with Fully Sharded Data Parallelism (FSDP) on 8 × NVIDIA A100 80GB GPUs. To isolate dataset effects, we fix SFT hyperparameters per model across all experiments. For Llama-3.1-8B, we adopt the same hyperparameters as in Lambert et al. [7], and for SmolLM2-1.7B, we follow Allal et al. [13]. Table 14 provides the SFT training configurations for both models.

## **E.1.2** Direct Preference Optimization (DPO)

For DPO, we choose the preference mixture <sup>10</sup> created by Lambert et al. [7], which is a curated blend of *on-policy* and *off-policy* preference data, synthetic instruction following augmentations, WildChat [8] conversational pairs, cleaned UltraFeedback [47] data, and a small Persona IF [63] subset, designed to balance broad performance and targeted instruction following under the DPO objective. We use the same hyperparameters from [7]. We set the KL-penalty coefficient (referred to as dpo\_beta in *Open-Instruct*) to 5 and use the length-normalized DPO loss (dpo\_loss\_type=norm), following the recommendation in Lambert et al. [7]. We apply DPO on models that have already been fine-tuned via SFT using the Tulu, SmolTalk, and TuluTalk datasets. The full set of DPO hyperparameters is provided in Table 14.

### **E.2** Evaluation Setup

We assess model performance using the *LM Evaluation Harness* framework [28], a widely adopted standard for evaluating language models across diverse benchmark suites. To ensure a comprehensive and task-diverse evaluation, we include benchmarks spanning *Knowledge* (e.g., MMLU [77], TruthfulQA [78]), *Reasoning* (e.g., BBH [79], ARC-C [80]), *Commonsense Understanding* (e.g., HellaSwag [81], WinoGrande [82]), *Instruction Following* (e.g., IF-Eval [83]), *Mathematical Reasoning* (e.g., GSM8K [84], MATH [85]), and *Coding* (e.g., HumanEval, HumanEval+ [86]). We further include benchmarks from *Open LLM Leaderboards* [17, 18] to gauge general instruction performance under competitive public standards. This setup ensures a fair, fine-grained comparison between models and data mixtures, highlighting both strengths and failure modes across capabilities.

<sup>9</sup>https://github.com/allenai/open-instruct

<sup>10</sup> https://huggingface.co/datasets/allenai/llama-3.1-tulu-3-8b-preference-mixture

Table 14: Training hyperparameters for SFT and DPO on Llama-3.1-8B and SmolLM2-1.7B.

	S	FT	DPO		
Parameter	Llama-3.1-8B	SmolLM2-1.7B	Llama-3.1-8B	SmolLM2-1.7B	
Total Batch Size	128	128	128	128	
Per-Device Batch Size	1	1	1	1	
Gradient Accumulation Steps	16	16	16	16	
Max Sequence Length	4096	8192	2048	2048	
Number of Epochs	2	2	1	1	
Learning Rate	$5 \times 10^{-6}$	$3 \times 10^{-4}$	$5 \times 10^{-7}$	$5 \times 10^{-7}$	
LR Scheduler	Linear	Cosine	Linear	Linear	
Warmup Ratio	0.03	0.10	0.10	0.10	
Weight Decay	0.0	0.0	0.0	0.0	

#### E.3 Additional Results

#### E.3.1 SFT with Tulu+SmolTalk Mixture

Table 15 presents additional experiments using a naïve data mixture formed by directly concatenating the full Tulu and SmolTalk datasets (denoted as Tulu+SmolTalk). This results in an (uncurated) corpus of approximately 1.979 million samples.

For the Llama model, the naïve mixture performs slightly better than Tulu but worse than SmolTalk. It achieves the best scores on IF-Eval (74.94%) and GSM8K (77.03%) but underperforms on reasoning tasks (ARC, BBH, MuSR), commonsense tasks (HellaSwag, WinoGrande), and MMLU. In coding benchmarks, it offers no meaningful gains over Tulu and remains significantly behind SmolTalk.

For the SmolLM model, Tulu+SmolTalk slightly outperforms both Tulu and SmolTalk, with the most notable improvement on GSM8K (56.07%). However, the overall performance gain is marginal, only 0.24% higher than SmolTalk and thus indicating that this naïve mixture, despite doubling the dataset size, lacks the benefit of thoughtful curation.

These results underscore that simply merging two strong datasets does not guarantee performance improvements. In contrast, our systematic and principled curation based on quality and diversity yields the size-efficient *TuluTalk* mixture which outperforms both Tulu and SmolTalk, as well as the naïve Tulu+SmolTalk combination, in overall average and across many benchmarks for both models.

### E.3.2 SmolLM Performance on Code Benchmarks

In Tables 1 and 3 of the main paper, as well as the supplemental results in Table 15, the SmolLM model shows identical, low scores across all dataset variants on the HumanEval and HumanEval+ coding tasks. This suggests that the model fails to generalize meaningfully to code-related benchmarks and likely resorts to template-based or fallback completions. Examples of such behavior include emitting empty function stubs or default print statements. These outputs rarely match the required semantics of the prompt, leading to consistently low pass@1 scores, which measure exact functional correctness on the first attempt. These results highlight the capacity limitations of the smaller SmolLM architecture, which was explicitly designed to prioritize conversational fluency over structured reasoning. This limitation becomes especially apparent given that the same SmolTalk dataset improves coding performance when used to train the larger Llama model. Furthermore, the same pattern holds for the Tulu and Orca datasets: while SmolLM continues to underperform on code benchmarks, the same datasets yield clear improvements when used to train the larger Llama model.

Table 15: SFT results for Llama-3.1-8B and SmolLM2-1.7B base models fine-tuned on Tulu (939k samples), SmolTalk (1.04m samples), a naïve concatenation of the two (Tulu+SmolTalk; 1.979m samples), and our curated *TuluTalk* (808k samples), evaluated on the Open LLM Leaderboards (averaged) and code benchmarks. The overall average is across all benchmarks. **Bold** marks the row-wise best score. Color-shaded columns highlight the superior TuluTalk model.

		Llam	a-3.1-8B		SmolLM2-1.7B			
Benchmark	Tulu	SmolTalk	Tulu + SmolTalk	TuluTalk	Tulu	SmolTalk	Tulu + SmolTalk	TuluTalk
Knowledge								
MMLU (5-shot)	62.90	62.88	62.68	63.91	49.71	47.88	49.61	49.34
MMLU-Pro (5-shot)	28.73	31.76	28.49	30.17	19.61	20.37	20.25	20.67
TruthfulQA (0-shot)	46.41	55.74	51.57	53.16	44.04	44.74	42.12	43.65
GPQA (0-shot)	27.77	28.78	28.02	29.28	27.85	27.60	26.59	27.68
Reasoning								
ARC-C (25-shot)	54.61	59.04	54.44	57.42	44.54	48.46	46.59	47.27
BBH (3-shot)	39.06	45.50	44.99	43.50	36.66	37.81	38.29	38.33
MuSR (0-shot)	42.86	38.49	39.76	40.62	33.33	33.86	34.39	33.28
Commonsense								
HellaSwag (10-shot)	60.87	61.54	61.14	62.98	51.01	52.10	50.80	51.36
WinoGrande (5-shot)	76.64	77.19	76.40	79.22	65.90	65.27	65.59	66.06
Instruction Following	70.01	77.17	70.10	,,,,,,	03.70	03.27	05.57	00.00
IF-Eval (0-shot)	74.09	74.51	74.94	74.84	60.25	56.83	60.73	60.85
` '	74.09	74.31	74.54	74.04	00.23	30.63	00.73	00.03
Math	74.07	7475	<b>55</b> 02	74.04	10.12	50.46	54.05	54.10
GSM8K (5-shot)	74.37	74.75	77.03	74.84	49.43	52.46	56.07	54.13
MATH (4-shot)	12.31	10.42	10.20	11.96	6.27	5.89	5.51	6.16
Code								
HumanEval (pass@1)	58.54	54.51	55.88	56.49	1.83	1.83	1.83	1.83
HumanEval+ (pass@1)	45.37	44.27	44.88	44.33	1.83	1.83	1.83	1.83
Leaderboards								
Open LLM Leaderboard 1	62.63	65.19	63.88	65.26	50.77	51.82	51.80	51.97
Open LLM Leaderboard 2	37.47	38.24	37.73	38.40	30.66	30.39	30.96	31.16
Overall	50.32	51.38	50.74	51.62	35.16	35.49	35.73	35.89

### **E.3.3** Efficiency Gains

To assess efficiency and training cost, we report the number of processed tokens (computed with each model's distinct tokenizer), estimates for training FLOPs, and total GPU hours (on an 8 x A100 GPU cluster) in Table 16 for SFT training of Llama-3.1-8B and SmolLM-2-1.7B models on Tulu, SmolTalk, and TuluTalk. We find that the reduction in dataset size translates approximately linearly into efficiency gains. For example, TuluTalk is around 14% smaller than Tulu. For Llama, this results in a proportionate reduction in the number of processed tokens (708M compared to 835M), ExaFLOPs (34 compared to 40), and total GPU hours (38 compared to 45). Similar trends are observed for the SmolTalk dataset and for the SmolLM model. These additional experiments validate the efficiency improvements achieved by our curated TuluTalk dataset.

Table 16: Comparison of SFT training efficiency for Llama-3.1-8B and SmolLM2-1.7B on Tulu, SmolTalk, and TuluTalk. We report processed tokens (per tokenizer), estimated ExaFLOPs, and GPU hours (excluding the initial warmup phase). Lower is better (\$\psi\$).

		Llama-3.1-	8B	SmolLM2-1.7B			
Metric	Tulu	SmolTalk	TuluTalk	Tulu	SmolTalk	TuluTalk	
Tokens (↓) ExaFLOPs (↓) GPU Hours (↓)	835M 40.1 45	875M 42.0 49	708M 34.0 38	910M 9.28 26	961M 9.80 28	782M 7.98 22	

#### E.3.4 Performance Results for Diverse Models and Scales

To demonstrate the effectiveness and generalizability of TuluTalk across different architectures and scales, we provide results for three additional models: Qwen2.5-0.5B and Qwen2.5-3B [22], as well as for SmolLM3-3B [31], covering small- to mid-scale models of different architectures.

Tables 17 and 18 report evaluation results across all considered benchmarks. In general, the results are in line with the observations in our main body and show that our curated TuluTalk SFT dataset achieves better performance compared to Tulu and Smoltalk, while being a leaner dataset overall. These additional results demonstrate the generalizability of both TuluTalk and our curation recipe across model architectures and scales. While evaluating larger models like Qwen2.5-32B would be informative, our computational setup and budget unfortunately limits us from training larger models.

Table 17: Results for Qwen2.5-0.5B and Qwen2.5-3B fine-tuned on Tulu, SmolTalk, and TuluTalk, evaluated on the Open LLM Leaderboards and code benchmarks. The overall average is across all benchmarks. **Bold** marks the row-wise best score. Color-shaded columns highlight TuluTalk models.

	Qwen2.5-0.5B				Qwen2.5-3B			
Benchmark	Base	Tulu	SmolTalk	TuluTalk	Base	Tulu	SmolTalk	TuluTalk
Knowledge								
MMLU (5-shot)	46.51	45.67	43.25	44.65	65.55	66.09	65.80	65.03
MMLU-Pro (5-shot)	16.98	14.14	13.15	13.89	32.12	32.56	32.00	31.62
TruthfulQA (0-shot)	39.78	39.99	40.87	39.46	48.87	46.85	50.68	48.76
GPQA (0-shot)	27.20	24.33	25.59	25.59	28.27	26.43	27.35	28.19
Reasoning								
ARC-C (25-shot)	32.22	31.83	31.66	32.59	52.90	52.29	51.34	52.32
BBH (3-shot)	31.58	30.79	29.53	29.70	46.38	45.20	43.03	45.88
MuSR (0-shot)	34.26	32.01	32.41	32.54	43.25	41.14	39.77	42.83
Commonsense								
HellaSwag (10-shot)	39.93	39.10	38.70	39.18	55.51	56.65	54.97	56.40
WinoGrande (5-shot)	56.75	58.33	57.14	57.83	71.35	72.06	70.24	72.09
Instruction Following								
IF-Eval (0-shot)	17.34	40.60	35.59	43.24	27.13	63.44	61.50	66.75
Math								
GSM8K (5-shot)	34.50	37.30	41.93	41.47	70.20	74.21	77.33	77.10
MATH (4-shot)	4.68	6.50	5.21	5.59	15.63	21.00	16.99	18.67
Code								
HumanEval (pass@1)	28.66	28.66	27.44	27.44	38.41	44.34	41.22	42.68
HumanEval+ (pass@1)	26.22	25.00	24.39	24.39	32.93	39.12	34.27	36.85
Leaderboards								
Open LLM Leaderboard 1	41.62	42.04	42.26	42.53	60.73	61.36	61.73	61.95
Open LLM Leaderboard 2	22.01	24.73	23.58	25.09	32.13	38.29	36.77	38.99
Overall	31.19	32.45	31.92	32.68	44.89	48.67	47.61	48.94

Table 18: Results for SmolLM3-3B fine-tuned on Tulu, SmolTalk, and TuluTalk, evaluated on the Open LLM Leaderboards and code benchmarks. **Bold** marks the row-wise best score. The color-shaded column highlights TuluTalk.

Benchmark	Base	Tulu	SmolTalk	TuluTalk
Knowledge				
MMLU (5-shot)	61.37	61.10	59.96	61.55
MMLU-Pro (5-shot)	33.55	28.86	31.14	31.80
TruthfulQA (0-shot)	45.91	45.98	49.87	49.19
GPQA (0-shot)	29.70	28.61	30.54	29.85
Reasoning				
ARC-C (25-shot)	56.06	53.75	58.53	58.38
BBH (3-shot)	45.57	44.52	44.68	44.19
MuSR (0-shot)	41.80	40.61	39.38	40.30
Commonsense				
HellaSwag (10-shot)	57.24	55.49	56.22	56.74
WinoGrande (5-shot)	72.77	73.16	72.38	74.03
Instruction Following				
IF-Eval (0-shot)	19.52	65.78	56.89	63.20
Math				
GSM8K (5-shot)	67.10	70.32	73.36	72.55
MATH (4-shot)	16.92	19.49	20.62	19.73
Code				
HumanEval (pass@1)	37.20	47.44	45.24	44.76
HumanEval+ (pass@1)	29.88	32.44	31.10	30.46
Leaderhoards	27.00	02	31.10	50.10
Open LLM Leaderboard 1	60.08	59.97	61.72	62.07
Open LLM Leaderboard 2	31.18	37.98	37.21	38.18
Open ELW Leaderboard 2	31.10	31.90	31.21	30.10
Overall	43.90	47.68	47.85	48.34

### E.3.5 Performance Results for SFT and DPO for Llama-3.1-8B

To assess whether our SFT curation insights transfer to preference-tuned models, we also apply DPO on Llama models fine-tuned on Tulu, SmolTalk, and our proposed TuluTalk mixture. Table 19 reports DPO and SFT performance results across benchmarks for the Llama-3.1-8B base model, fine-tuned on all datasets under consideration and DPO-tuned using the same preference mixture proposed by Lambert et al. [7].

For both Tulu and SmolTalk, DPO leads to notable improvements on TruthfulQA, all reasoning benchmarks, HellaSwag, and especially instruction following. For Tulu, math performance shows a mixed trend: GSM8K scores decrease slightly, while MATH improves significantly. This effect is not observed for SmolTalk, where math performance remains largely unchanged. Coding performance declines slightly for both datasets, while both Open LLM Leaderboard scores increase noticeably.

Importantly, the performance gains observed for our proposed *TuluTalk* under SFT carry over to the DPO setting. Specifically, TuluTalk achieves the highest overall average under DPO (53.08%), outperforming Tulu (51.89%) and SmolTalk (52.96%), and improving upon the base model by over 11%. These gains are observed across evaluation categories, including instruction following, reasoning, and commonsense understanding, highlighting the consistency of performance gains across model sizes and families.

Notably, the DPO-TuluTalk model achieves the best IF-Eval score (81.51%) and leads on HellaSwag and Open LLM Leaderboard 1. This suggests that our mixture not only improves factual accuracy and instruction compliance, but also enhances performance on alignment-sensitive public benchmarks.

Overall, these results confirm that our principled, quality- and diversity-driven curation, with attention to instruction following signals, response quality, and task diversity, not only yields performance gains under SFT, but also that these gains transfer to DPO.

Table 19: Performance of Llama-3.1-8B (base) fine-tuned via SFT or DPO on Tulu, SmolTalk, and TuluTalk, evaluated on Open LLM leaderboards, code benchmarks, and reasoning tasks. The overall average is across all benchmarks. **Bold** marks the row-wise best score. Color-shaded columns highlight the superior TuluTalk model under each training method.

			SFT		DPO		
Benchmark	Base	Tulu	SmolTalk	TuluTalk	Tulu	SmolTalk	TuluTalk
Knowledge							
MMLU (5-shot)	65.03	62.90	62.88	63.91	62.09	63.30	62.58
MMLU-Pro (5-shot)	32.71	28.73	31.76	30.17	29.75	32.58	31.32
TruthfulQA (0-shot)	45.22	46.41	55.74	53.16	56.28	62.45	61.67
GPQA (0-shot)	31.46	27.77	28.78	29.28	29.28	30.70	28.69
Reasoning							
ARC-C (25-shot)	54.69	54.61	59.04	57.42	57.85	61.12	60.75
BBH (3-shot)	46.48	39.06	45.50	43.50	40.74	46.50	44.91
MuSR (0-shot)	37.96	42.86	38.49	40.62	40.61	39.15	39.02
Commonsense							
HellaSwag (10-shot)	61.44	60.87	61.54	62.98	65.48	66.38	68.64
WinoGrande (5-shot)	76.87	76.64	77.19	79.22	74.74	76.95	79.01
Instruction Following							
IF-Eval (0-shot)	12.45	74.09	74.51	74.84	80.51	79.16	81.51
Math							
GSM8K (5-shot)	50.64	74.37	74.75	74.84	69.45	75.74	74.75
MATH (4-shot)	5.97	12.31	10.42	11.96	20.85	12.61	13.52
Code							
HumanEval (pass@1)	34.76	58.54	54.51	56.49	56.10	54.15	55.66
HumanEval+ (pass@1)	28.66	45.37	44.27	44.33	42.76	40.61	41.10
Leaderboards							
Open LLM Leaderboard 1	58.98	62.63	65.19	65.26	64.32	67.66	67.90
Open LLM Leaderboard 2	27.84	37.47	38.24	38.40	40.29	40.12	39.83
Overall	41.74	50.32	51.38	51.62	51.89	52.96	53.08

# F Limitations and Broader Impact

**Limitations.** While our study provides a comprehensive and principled analysis of post-training SFT datasets, a few limitations remain. First, our annotations rely on the Magpie framework, which uses the LLM-as-a-judge technique to score various aspects such as prompt quality, response helpfulness, and safety. Although we enhance Magpie with error-tolerant parsing and extend it for multi-turn support, the subjectivity inherent in LLM-based judgments may introduce variance in label quality. In addition, annotations reflect the capabilities and biases of the underlying judge model, which may shift as stronger evaluators emerge. Nonetheless, the consistency of observed trends and performance gains across benchmarks suggests that our annotations, generated using a capable Llama-3.3-70B-Instruct judge, are robust and highly informative for practical curation. Second, while our analysis focuses on the SFT stage, evaluating and comparing data quality for preference tuning remains an important direction for future work, particularly as the variety of training recipes used in preference tuning makes dataset comparisons more challenging. Third, when designing TuluTalk, we perform a limited number of ablations for balancing task diversity due to computational constraints. It is interesting to perform additional data mixture ablations to enhance the performance of TuluTalk. Finally, as TuluTalk is derived from the open-source Tulu and SmolTalk datasets, it inherits any existing biases and limitations present in those corpora, such as a predominant focus on English and limited coverage of specialized skills like tool use.

**Broader Impact.** By open-sourcing detailed annotations, curated data mixtures, and reproducible recipes, our work lowers the barrier to high-quality post-training research and promotes transparency in dataset design. Our quality annotations of Tulu and SmolTalk can be leveraged by both researchers and practitioners to conduct further analyses or construct data mixtures tailored to their specific use cases. *TuluTalk*, our curated dataset, achieves top-tier performance with substantially fewer samples, offering improvements in both compute efficiency during SFT and downstream performance. While we apply our curation recipe on Tulu and SmolTalk, our quality-based and diversity-driven curation recipe can be used with any datasets in principle. Even though the datasets we build on are derived from open and broadly safe sources, we acknowledge that any general-purpose LLM corpus carries dual-use risk. We encourage responsible use and support future work that incorporates adversarial safety evaluations and multilingual fairness into post-training pipelines.

Contributions. This work presents a rigorous and reproducible investigation into the effects of post-training data quality on LLM performance. We evaluate two widely used model architectures, Llama-3.1-8B and SmolLM2-1.7B, across a broad suite of benchmarks, including instruction following, coding, math, and reasoning. Grounded in systematic Magpie-based annotations, our study offers the first side-by-side dissection of Tulu and SmolTalk, revealing critical differences in data quality and task composition. Leveraging these insights, we curate *TuluTalk*, a lean and high-performing dataset that outperforms both Tulu and SmolTalk on several key benchmarks. Furthermore, we demonstrate that the performance benefits of our curated dataset generalize beyond SFT, consistently translating into gains under DPO as well, underscoring the robustness of our data-centric approach across alignment methods. Our methodology combines principled annotation, quality filtering, and task-aware rebalancing, complemented by an extensive and transparent analysis in the appendix, to establish a strong and reusable foundation for future post-training research.